USING INFORMATION ON PAST AND PRESENT FOREST COVER TO GUIDE RESTORATION EFFORTS: AN ANALYSIS OF DATA QUALITY AND LANDSCAPE CONNECTIVITY IN UNAMA'KI (CAPE BRETON, NOVA SCOTIA)

by

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Dalhousie University is located in Mi'kma'ki, the ancestral and unceded territory of the Mi'kmaq. We are all Treaty people.

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ABSTRACT

Ecological connectivity is the extent to which a landscape supports the movement of organisms and processes between patches of suitable habitat and is necessary for ecosystem functioning. Boreal forests in Unama'ki (Cape Breton, Nova Scotia) have experienced reductions in connectivity in recent decades due to an outbreak of spruce budworm and subsequent over browse by moose. Using landcover data from Parks Canada, I analysed present and historical boreal forest connectivity in northwestern Unama'ki. I found that forest stands prior to the outbreak had on average a larger area and perimeter ($p<0.05$). I identified and prioritized non-forested areas for treeplanting in Zonation software. I developed a novel, user-friendly approach to assess data quality that can be used to assess data suitability and contextualize model results to end users. Information from this research can be used to support ongoing treeplanting efforts to restore connectivity, including in parks and protected areas.

LIST OF ABBREVIATIONS USED

ABF	Additive Benefit Function
ACCDC	Atlantic Canada Conservation Data Centre
ANOVA	One-way Analysis of Variance
CAZ	Core-area Zonation
CBHNP	Cape Breton Highlands National Park
DaFFU	Data fitness-for-use
df	Degrees of Freedom
EQDaM	External Quality of Spatial Data from Metadata
GBIF	Global Biodiversity Information Facility
GIS	Geographic Information Systems
ha	Hectare(s)
HSD	Honestly Significant Difference
IBM	International Business Machines Corporation
IPCA	Indigenous Protected and Conserved Areas
km	Kilometre(s)
m	Metre(s)
MCDM	Multiple criteria decision making
mm	Millimetre(s)
MMU	Minimum mappable unit
NPI	Normalized Perimeter Index
NS	Nova Scotia
SBW	Spruce Budworm
SPSS	Statistical Package for Social Sciences
STAAq	Spatial, Temporal, Aptness, and Application Assessment
std dev	Standard deviation
UNDRIP	United Nations Declaration on the Rights of Indigenous Peoples

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I feel grateful to be able to live, work and play on the unceded territory of Mi'kma'ki. I have learned so much through my time in the Wabanaki forest and am indebted to these lands' original stewards.

Thank you, Dr. Alana Westwood, for sharing your knowledge, guidance, and mentorship with me, both in academia but also in life generally. The safe space you foster in the Westwood Lab is special and I am grateful to have been involved. Thank you to all the members of the lab who consistently showed up for each other and provided support.

I am very lucky to have such a strong community of friends and family whom I love. To everyone who has shared their time and energy with me, be it through work sessions, climbing or just cooking together, I am so grateful.

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It is ironic than in a time of total climate collapse, nature is my most reliable source of comfort. So finally, thank you to the trees, rivers, flowers, and rocks. It is a privilege to dedicate my career to learning about and caring for you.

LAND ACKNOWLEDGEMENT

Unama'ki is one of seven districts in Mi'kma'ki, the unceded and ancestral land of the Mi'kmaq. Mi'kma'ki is governed by the Peace and Friendship treaties, which did not cede or surrender Mi'kmaq rights to the land but in fact stated their rights to hunt, fish and earn a moderate livelihood from the land (Government of Canada - Indigenous Relations and Northern Affairs, 2008). The Mi'kmaq have stewarded these lands since time immemorial and as a settler treaty person living in Turtle Island, I recognize my responsibility to act in accordance with Truth and Reconciliation.

The Landsat satellite imagery that the forest cover data in Chapter 3 is based on is widely used in spatial analyses (Wulder et al., 2022). However, as far as can be understood from the literature, the imagery was captured without the prior informed consent of the Mi’kmaq, the ancestral stewards of Unama’ki. Providing free, prior informed consent is a core principle in the United Nations Declaration on the Rights of Indigenous Peoples (UNDRIP; United Nations, 2008) and OCAP® (Ownership, Control, Access and Possession) guidelines (The First Nations Information Governance Centre, 2014). I acknowledge that this issue is persistent in satellite imagery and remote sensing analyses, as well as my own limitation to address this issue as it is outside the scope of this thesis. It is my hope that this research can nonetheless support current ongoing efforts within Unama’ki to establish Indigenous Protected and Conserved Areas (IPCAs).

STATEMENT

Research can and must not be considered outside the influence of the researcher. One’s positionality (identity, life history, values, etc.) will inevitably have an effect on the work they produce. I am a settler of predominantly Irish descent living in Mi’kma’ki and was raised on the traditional territory of the Mississaugas of the Credit, the Anishnabeg, the Chippewa, the Haudenosaunee and the Wendat peoples, in what is also known as Toronto. I proudly identify as queer and hold community, sustainability, and joy as core values. I am privileged to have many experiences working, learning, and playing in the forests of Mi’kma’ki that have facilitated my respect for nature, which I hope translates in this research.

CHAPTER 1 INTRODUCTION

1.1 FORESTS AND CONNECTIVITY

Boreal forests make up 27% of the world's forest area (FAO, 2020) and are Canada's largest biome. Limited to northern circumpolar regions, boreal forests are dominated by species within the *Abies, Larix, Picea, Pinus, Populus* and *Betula* genera (Brandt, 2009) and successional dynamics are influenced by fire, insects and disease (Brandt et al., 2013). Boreal forests provide vital services including water regulation and filtration, carbon sequestration and storage, erosion control, habitat for wildlife, nutrient cycling, cultural and recreational opportunities, and materials (such as lumber and pulp), to name a few (Anielski & Wilson, 2005). The boreal forest biome is under stress due to warming temperatures (Henry, 2005), non-native species (Langor et al., 2014) and particularly an increase in human resource extraction and development (Gauthier et al., 2015; Kreutzweiser et al., 2013; Schindler & Lee, 2010).

Watson et al. (2018) summarize the importance of intact and connected forest ecosystems to climate regulation, watershed services, biodiversity, Indigenous peoples and human health. Ecological connectivity is a measure of the extent to which a landscape supports the movement of organisms and ecological processes within and between patches of suitable habitat (Taylor et al., 1993). Inversely, fragmentation is the breaking up of contiguous habitat into isolated patches (Haddad et al., 2015). Although fragmentation caused by natural disturbance (insect outbreak, fire) is a regular occurrence in the boreal forest biome, intensive forestry and anthropogenic development have accelerated and intensified this fragmentation (Boucher et al., 2009; Stanojevic et al., 2006; Wulder et al., 2011). Reforestation, the restoration of previously forested areas, is touted as an efficient tool to combat the impacts of fragmentation (FAO and UNEP, 2020). Planting efforts focused to connect isolated patches of forest have been shown to drastically increase ecosystem services provided by the forested landscape (Huang et al., 2022).

1.1.1 Forests in Unama'ki

Unama'ki (Cape Breton, Nova Scotia) is one of seven districts in Mi'kma'ki, the unceded and ancestral land of the Mi'kmaq (Figure 1.1). Boreal forests in Unama'ki have undergone significant forest loss and are considered fragmented (Bouman et al., 2005). Successional pathways of boreal forests in Unama'ki are naturally controlled by spruce budworm (*Choristoneura fumiferana (Clemens)*; SBW) outbreaks (Baskerville, 1975) which defoliate and kill predominantly balsam fir (*Abies balsamea* (L.) Mill.) and white spruce (*Picea glauca* (Moench) Voss) trees (Government of Canada, 2013). The most recent large outbreak of spruce budworm was seen in the late 1970s (Ostaff & MacLean, 1989).

Following this outbreak, western moose (*Alces alces andersonii* Peterson) began browsing on the regenerating saplings. The western moose subspecies were introduced to the Cape Breton Highlands National Park (CBHNP; or the Park) in the late 1940s from western Canada (Lothian, 1976) following the extirpation of the native eastern moose subspecies (*Alces alces americana* Clinton) around the 1930s (Bridgland et al., 2007). Moose populations in Cape Breton Highlands National Park, grew from an estimated 215 individuals in 1977 (Couchie & Baldwin, 1977; Prescott, 1979 as cited in Bridgland et al., 2007), to 1,126 in 1985 (Wentzell, 1985 cited in Bridgland et al., 2007). Moose abundance reached a high of 4.2 moose/km^2 in 2004, and dropped below 2.0 moose/km^2 in 2006 (R. Smith et al., 2015). Their abundant population led to over browsing of regenerating stands, many of which converted to grasslands (C. Smith et al., 2010) . However, there is no known research on whether the western moose subspecies behaves significantly differently in this region than the eastern moose subspecies did in the past, and the extent of browsing pressure may not be related to the subspecies but rather an elimination of moose predators.

Caribou (*Rangifer tarandus* C.H. Smith) were also once found throughout the boreal forest of Unama'ki but were extirpated in the early 1900s (Bergerud & Mercer, 1989).

Caribou fill a different niche than moose in that they eat lichen found in mature coniferous forests, while moose prefer to browse on shrubs and saplings (Christopherson et al., 2019). A reintroduction of 51 caribou into Cape Breton Highlands National Park in 1968 and 1969 was unsuccessful, likely due in large part to both the spread of brain worm, *Parelaphostrongylus tenuis*, which causes pathological conditions, and insufficient habitat (Bergerud & Mercer, 1989).

In addition to moose browse, large tracts of boreal forest impacted by the SBW outbreak were salvage logged to minimize lost profits (Nova Scotia Department of Natural Resources, 1994). Salvage logging removed large amounts of tree biomass and resulted in the creation of road networks. This loss and fragmentation of boreal forest limited the services provided by intact boreal forest cover, but also the combined disruption of over browsing and logging may have led to a decrease in species that rely on mature boreal forests for habitat, including the provincially listed at-risk American marten (*Martes americana* Turton; Scott, 2001) and Canada lynx (*Lynx canadensis* Kerr) and provincially and federally listed Bicknell's thrush (*Catharus bicknelli* Ridgway; D'Orsay & Howey, 2020).

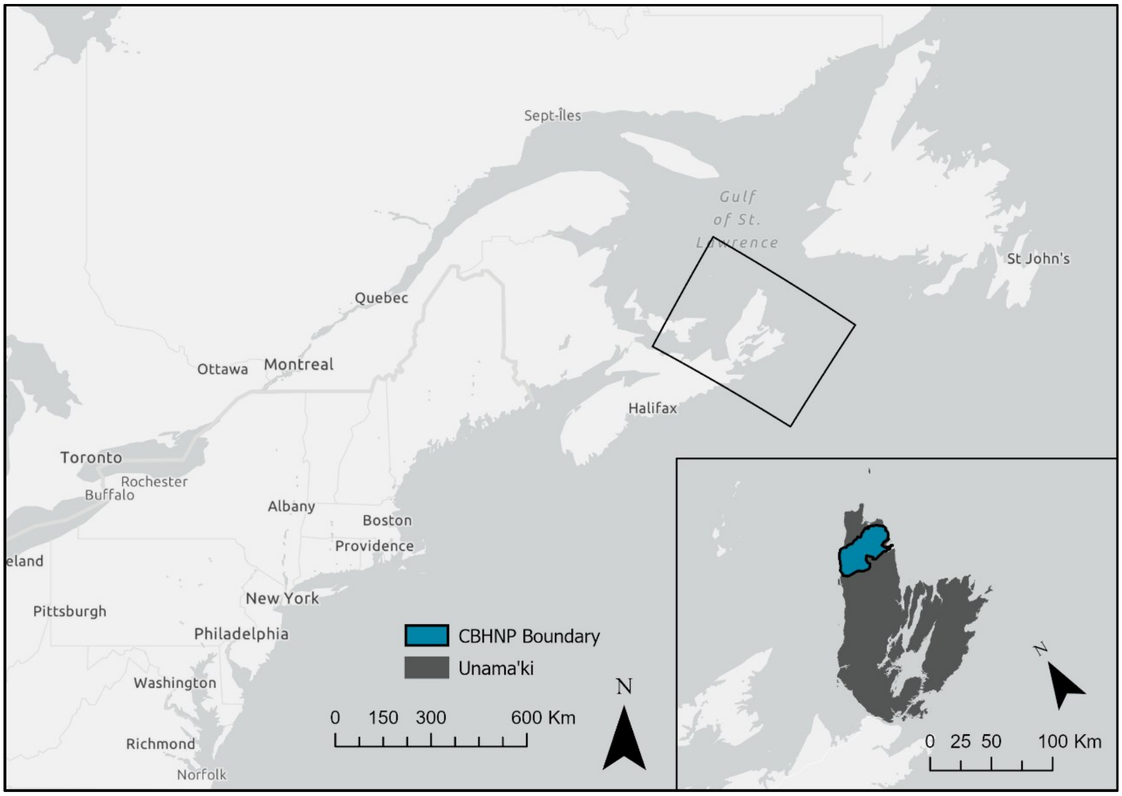

Figure 1.1 Reference map of eastern North America with an inset map highlighting Unama'ki in grey and Cape Breton Highlands National Park (CBHNP) in blue.

The Park has applied control measures such as building moose exclosures and organizing a moose harvest conducted by Mi'kmaw communities in Unama'ki (D'Orsay & Howey, 2020; R. Smith et al., 2015). The goal of these measures was to minimize further moose browse and allow the forest to regenerate naturally. However, it is possible that areas converted to grasslands have reached a new stable ecological state and may not revert to boreal forest cover unless more proactive measures are taken (C. Smith et al., 2010). Parks Canada has therefore also begun forest restoration through a tree planting program to increase the number of balsam fir and white spruce saplings (D'Orsay & Howey, 2020). Given limited resources and capacity, the Park is interested in focusing their tree planting efforts to areas that will restore historical connectivity.

Restoration ecology is a branch of ecology that studies interactions within and among ecosystems, in a restoration context (Palmer et al., 2016). Ecological restoration often occurs when an ecosystem has been disturbed or otherwise altered so that its structure or function is impacted (Palmer et al., 2016). Reference conditions can either be the state of an ecosystem prior to disturbance or some ideal ecosystem state which restoration efforts seek to recreate (Alagona et al., 2012; Palmer et al., 2016). Historical data on ecosystem structure and function is often used as a reference, however it is recommended historical conditions not be used as an exact target but as a guide for restoration broadly (Higgs et al., 2014). In this case, the Park is aiming to restore historical forest connectivity by planting trees in areas previously considered connected.

1.1.2 Modelling ecological connectivity

Ecological restoration requires robust data and analysis upon which to base decisions. Several methods exist to model habitat connectivity to inform conservation efforts. Common software packages and algorithms used for this task include the least-cost path function within ArcGIS Pro (2020a), Circuitscape (Anantharaman et al., 2020), Zonation (Moilanen, 2014), and Marxan (Ball et al., 2009). (Table 1.1 summarizes the use, benefits, and limitations of each). Least-cost path identifies a path of least resistance between a source and target area. Resistance is calculated from input features which often reflect an organism's response to different landcover types. This can be used to understand how species are likely to move through a landscape (Etherington, 2016). Circuitscape software uses circuit theory to understand and quantify connectivity (McRae et al., 2008) and is used to identify multiple corridors and pinch points between existing patches of habitat to guide conservation (e.g. Brodie et al., 2015; Dickson et al., 2013). Zonation is a spatial prioritization software that ranks features in a landscape based on various metrics including by maximizing patch size and regulating shape of cells in the study area according to habitat quality and incorporates connectivity into its algorithm. Zonation is often used in planning contexts such as to guide sustainable forestry (Westwood, Lambert, et al., 2020), protected area planning (Albert et al., 2017;

Lehtomäki et al., 2009) and conservation monitoring (Carroll et al., 2010) based on connectivity principles. Finally, Marxan analyses landscape data to delineate optimal areas for conservation. It is functionally similar to Zonation, however the user must set a minimum target (percent of the landscape) that the optimal area for conservation must meet, and is best applied to reserve network selection contexts (Watts et al., 2017).

Table 1.1 Summary of software and algorithms commonly used to model ecological connectivity.

Software	Main use	Benefits	Limitations
Circuitscape	Corridor design, protected area establishment, mapping gene flow.	Incorporates resistance surfaces. Analyzes infinite potential pathways. Highlights connectivity pinch points. Randomness of pathway selection reflects stochasticity in nature.	Assumes organisms do not change over time; cannot remember preferred pathways or change preference with age. Does not incorporate directional bias.
Least cost path (within ArcGIS Pro)	Ecological corridor mapping, protected area establishment.	Relatively simple model reduces computation time.	Only creates one low-cost path, in reality there may be many. Does not take width of corridor into account. Assumes organisms do not change over time; cannot remember preferred pathways or change preference with age.
Marxan	Protected area establishment.	Applicable for use in meeting political targets. Delineates several near-optimal protected areas.	Requires straightforward mathematical problems (exact costs, quantifiable target, etc.). Does not produce one best or most optimal solution.
Zonation	Protected area establishment, protected area monitoring, land management planning.	A variety of parametrization are available for connectivity. User assigns weights and whether to use targets. Outputs allow for detailed scenario comparison. Can account for climate change.	Subjectivity involved in determining weights of features.

Least-cost path is a very simple and effective method for use in rough estimations of corridor connectivity. However, I was not interested in identifying corridors between existing forest patches, but rather, looking to identify and quantify areas of historical connectivity to target restoration, making least cost path unapplicable. In addition, an exact proportion of the landscape to be restored has not been set, which means Marxan can not be applied. Circuitscape creates a comprehensive output of key corridors between known habitat patches. This analysis could highlight areas of connectivity at previous times that currently do not exist. However, the goal of this research is to determine priority areas of forest connectivity based on a combination of historical and present-day forest conditions. Focusing restoration to these priority historically connected areas ensures that restoration activity is concentrated in areas which previously supported similar forest cover. Therefore, Zonation's ability to rank cells according to their value to habitat quality and connectivity makes it the most applicable software for this research.

1.1.3 Data quality

While the method chosen to model tree planting prioritization influences the output, so too does the type and quality of the data incorporated into that model. Zonation analyses feature distribution data. A feature can include occurrences, a species distribution model, habitat type, roads, and so on (Moilanen et al., 2012). A Zonation model often includes several features of varying positive and/or negative weights according to the interests of the user (Moilanen et al., 2012).

Understanding and quantifying limitations of a dataset ensures results built on those data can be interpreted appropriately and may be considered more reliable (Powers & Hampton, 2019). Efforts to correct the inaccuracies inherent in spatial ecological data can be resource intensive, complicated and in some circumstances impossible. Modellers must therefore make every effort to at a minimum quantify and communicate such deficiencies and interpret results cautiously (Canfield et al., 2022).

1.2 RESEARCH OBJECTIVES

The overarching objective of my thesis is to analyse change in forest cover and connectivity through time in northwestwern Unama'ki to guide restoration efforts for boreal forest in this region. In Chapter 2, I evaluate existing methods to assess data quality for use in ecological modelling. I develop a new approach which builds on the strengths of pre-existing tools from other authors and proposes new modifications to address shortfalls in their application. I apply this method to related research work in Unama'ki as a case study. The tool for assessing data quality is later used in Chapter 3, the connectivity analysis. Chapter 3 can be broken down into three objectives: 3.1) Quantify forest cover change prior to and following the SBW outbreak; 3.2) Analyse forest connectivity across same time period; and 3.3) Highlight priority areas for tree planting based on historical forest cover.

To meet objective 3.1, I produce visualizations of forest loss at five time steps: 1972, 1989, 1999, 2009 and 2019, and compare the change within and outside of protected areas. I quantify change in average forest stand area, perimeter and normalized perimeter index (NPI) prior to and following the SBW outbreak. For objective 3.2, I produce models of forest connectivity at the above time steps to understand how landscape connectivity has changed through time. I analyze the distribution of priority areas within and outside protected areas. Finally, to meet objective 3.3, I develop a model of tree planting prioritization to guide restoration efforts, based on both present day and historical coniferous forest connectivity.

CHAPTER 2 ASSESSING SPATIAL DATA QUALITY FOR USE IN ECOLOGICAL MODELLING: AN ACCESSIBLE TOOL

2.1 INTRODUCTION

Ecological models are simulations which represent and predict interactions that occur in the natural world (IPBES, 2016). These models are used to better understand natural phenomena and are becoming an increasingly powerful component of decision making. An analysis of journals in Scopus indicates a steady increase in use of ecological models in peer-reviewed articles since the early 2000s, as well as an increase in the articles incorporating both models and decision making (Figure 2.1).

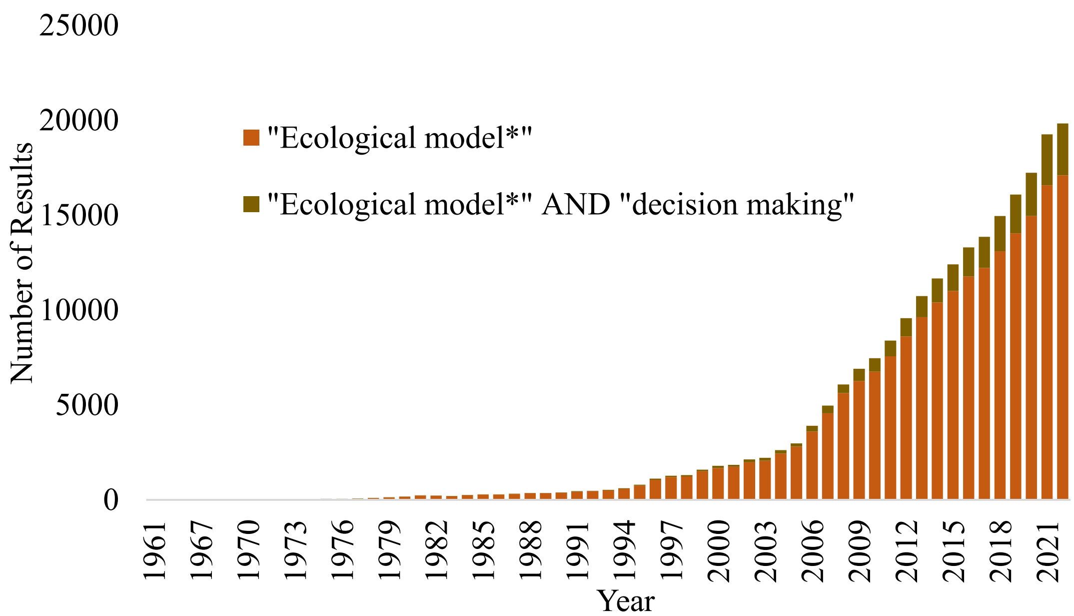

Figure 2.1 Results from query of Scopus database conducted in March 2022 for published articles that mention 1) "ecological model*" and 2) "ecological model*" AND "decision making" between 1961 and 2023. Documents from unrelated fields (such as medicine) were excluded.

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The increasing availability of spatial data (Farley et al., 2018) and advances in Geographic Information Science (GIS) and technologies (Song & Wu, 2021) make spatially-explicit ecological modelling a useful and reliable tool for research and decision-making. Though conceptually broad, spatial ecological models are used to answer various complex questions. For example, species distribution models are commonly used to better understand the environmental requirements of species (Cameron, 2021; Robinson et al., 2017) and identify areas of conservation value (Junker et al., 2012; Platts et al., 2010). Models of carbon sequestration potential are used to inform policy and land management (He et al., 2022; Lefebvre et al., 2020). Detailed reviews of other common ecological spatial model types are provided by Jackson et al. (2000), Jørgensen (2008), and Geary et al. (2020). Data included in ecological models can range from landcover type derived from satellite imagery, elevation, species occurrences collected through community science or surveys, to climate data such as precipitation, temperature measured at weather stations, and so on.

Variability and randomness inherent in ecological processes make accurately modelling such systems difficult. While it is impossible for model builders to remove uncertainty in their work, quantifying uncertainty can support estimation of model accuracy and inform decision-making about how to best use model outputs for management purposes (Gentil & Blake, 1981; Hamilton, 1991; Rykiel, 1996; van der Sluijs, 2002). There are a number of mathematical methods that estimate the statistical reliability of spatial models, which include the Monte Carlo simulation (Besag & Diggle, 1977) and sensitivity analyses (Hornberger & Spear, 1981), among others. Further, Van der Sluijs (2002) proposes a method of involving public stakeholders in the development and interpretation of models and their uncertainty.

In common with non-spatial models, a key component of the reliability and accuracy of a spatial model, is that the quality of input data strongly influences the output (Aerts et al., 2003; Beck et al., 2014; Lobo, 2008; Tessarolo et al., 2021). For example, spatial bias in sampling can distort patterns found in distribution models (Baker et al., 2022; Ballesteros-Mejia et al., 2013; Beck et al., 2014). Additionally, spatial autocorrelation measures the degree of similarity in nearby objects in a dataset, and can negatively influence the outcome of statistical tests (Lee, 2017). At worst, ecological models that use data that has not undergone a data quality assessment can lead to false assumptions and conclusions (Powers & Hampton, 2019). According to ISO 8402, quality is the “totality of characteristics of a product that bear on its ability to satisfy stated or implied needs” [*Quality Management and Quality Assurance (ISO 8402)*] (1994). Therefore an assessment of data quality must include information on both the data itself and the context in which it will be used (Devillers et al., 2002).

Data quality is understood in terms of the internal and external characteristics of a dataset. Internal data quality refers to the degree of error within a dataset, such as accuracy with respect to location and time, whether the feature is properly represented, logical consistency, and completeness (Gervais et al., 2009; Guptill & Morrison, 1995). External data quality, also known as fitness for use, is concerned with the specific needs of the user or research question and is often communicated through metadata (Gervais et al., 2009). For example, a user requires information on the positional accuracy of a dataset to determine if it meets their needs. If a user is interested in modelling plant species assemblages at a scale of a few metres squared, but data is only available at 30 m^2, the data is not fit for that use. External data quality varies depending on the application context, but is an important consideration for both data producers and users (Devillers et al., 2002).

Within the context of ecological modelling, common factors that influence data quality include the lack of standardization in data collection (Gula & Theuerkauf, 2013), data entry errors (Ley et al., 2019), and absence of sufficient metadata (Mayernik, 2019). Even if the dataset has a high level of internal quality, it may not have the appropriate external quality, or salience, to answer the desired research question or achieve the management objective. Many researchers have called for (e.g. Wu et al., 2022) and developed methods for measuring uncertainty in ecological spatial data, including efforts to account for spatial autocorrelation (F. Dormann et al., 2007) and validate crowd-sourced data (Goodchild & Li, 2012). Spatial autocorrelation is a measure of the degree to which spatially similar objects contain similar values (Griffith, 2005). However, statistical tests often rely on the assumption that all objects or values are independent of each other, and a data set found to have strong spatial autocorrelation may lead to inflated significance of statistical tests

(Griffith, 2005). Despite this, it is still common for spatial data to be collected and distributed without sufficient information on the uncertainty of the data either reported in the dataset itself or in ecological modelling efforts using those data (Hunter et al., 2009).

Furthermore, the recent increase in partnerships between Western researchers and Indigenous knowledge holders has been found to often be extractive and disproportionately benefit the researchers and not the knowledge holders themselves (Nadasdy, 1999). In the case of any coproduced research and co-management of resources, transparent and plain language summaries of results are key to successful partner engagement (Westwood, Barker, et al., 2020). We must therefore make every effort to quantify and communicate such deficiencies and interpret analyses cautiously. As with all science communication, it is necessary that this data quality assessment be accessible to diverse stakeholders, including those not directly involved in the creation of ecological data or models and/or those who do not have prior training in geospatial analysis.

The goal of this present exercise was to locate a tool which can evaluate spatial data for use in ecological modelling, and in the absence of finding such a tool, develop a new one. I defined the following criteria which the method must meet to be applicable to this research and for use by others in the field of ecological modelling:

1. Applicable to diverse model contexts and data types (e.g., community science data and protocol-based data).
2. Does not rely solely on evaluation of metadata.
3. Can be simply communicated to stakeholders not involved in the production of ecological data or models.

Ecological spatial models commonly incorporate datasets that represent a variety of phenomena, across many spatial and temporal scales (Coro et al., 2023). The tool therefore needed to be applicable to diverse datasets, including satellite imagery, community science observation and protocol-based data. Community science involves public participation in data collection and is becoming increasingly important in ecology (Shirk et al., 2012). In addition, the goal was to find a method that can be applied to nearly all ecological modelling analyses, and so should be flexible enough to be used in a variety of contexts. Metadata is the information about a dataset including how and when the data were produced, and is a key component of data sharing (Michener, 2015). However, metadata is often missing, incomplete, or is communicated in a way that is unhelpful or not understandable to the end-user (Boin & Hunter, 2008; Goodchild, 2007). The approach then had to be flexible and not depend solely on the presence of sufficient metadata. Finally, research has shown that data quality assessments are often too complex to be accessible to end users (Goodchild, 2007; Grira et al., 2013). The outcome of the evaluation needed to be understood by an end user who may not have specialized training in modelling, mathematics, or statistics.

Several methods exist, however I was unable to find a simple tool which met each of the above criteria. The development of a new approach was required and therefore became a component of this research. I discuss and analyze existing methods below, then introduce a new approach.

2.2 LOCATING EXISTING APPROACHES

In March of 2022, I conducted a scoping review of the Scopus database (*Scopus*, n.d.) to search for existing methods to evaluate spatial data quality. I found that several tools have been developed to communicate data uncertainty to stakeholders and data 'end users', as in those who are not involved in the development of a data analysis or model but who use and make decisions based on spatial data. Only methods which met one or more criteria and were published in peer-review journals were included. I describe and evaluate these here.

Pôças et al. (2014) developed an index called External Quality of Spatial Data from Metadata (EQDaM), to evaluate the quality of spatial data according to the needs of data users and their applications. The index is comprised of data quality indicators which an ideal dataset should meet based solely on its metadata (Pôças et al., 2014). The user defines these quality indicators based on the requirements of their analysis. A binary matrix ($C = [c_{i,j}]_{mn}$) is calculated where a dataset either meets a quality indicator (1) or does not (0), where $i = \{1, 2, ..., m\}$ rows, with m being the number of datasets, and $j = \{1, 2, ..., n\}$ columns, with n being the number of quality indicators. A dataset receives a value of 1 (meets quality indicatory) or 0 (does not meet quality indicator), as represented by: $c_{i,j} = \{0,1\}$. An overall fitness for use score (Q_i) is then determined using the following equation:

$$Q_i = \left(\frac{1}{n} \sum_{j=1}^{n} c_{i,j} \right) \times 100 \tag{1}$$

The approach introduces the use of critical factors which are indicators that if not met, disqualify the dataset for use. The user determines which quality indicators are considered critical factors. A dataset can be considered 1) unfit for use (a critical factor was not met); 2) partially fit for use (at least one indicator was not met, but all critical factors were met); or 3) fit for use (all indicators were met).

Wentz & Shimizu (2018) evaluate data quality through a multiple criteria decision making framework named data fitness-for-use (DaFFU). Unlike the model by Pôças et al. (2014), the tool created by Wentz & Shimizu (2018) does not rely solely on metadata to understand data quality. The method is designed to compare the quality of multiple datasets which represent the same feature to select the one most appropriate for the user's needs (Wentz & Shimizu, 2018). The user determines a set of criteria and assigns performance scores to each dataset according to how closely each criterion is met. Criteria can either be considered as a benefit (higher values are better) or a cost (lower values are better). Scores can be assigned as binary, ordinal (rank), or interval/ratio values which are then normalized. In addition, individual criteria can be weighted to place emphasis on certain data characteristics. Equations 2 and 3 below are the normalization equations for benefit and cost criteria, respectively. Where x_{ij} is the performance score and q_{ij} is the normalized value.

$$q_{ij} = \frac{x_{ij} - \min\limits_{i}(x_{ij})}{\max\limits_{i}(x_{ij}) - \min\limits_{i}(x_{ij})} \tag{2}$$

$$q_{ij} = \frac{x_{ij} - \max\limits_{i}(x_{ij})}{\min\limits_{i}(x_{ij}) - \max\limits_{i}(x_{ij})} \tag{3}$$

If weights are included, the normalized value is then multiplied by the corresponding weight for each criterion.

Fischer et al. (2021) describe a method called the Spatial, Temporal, Aptness, and Application Assessment (STAAq) which builds on the Wentz & Shimizu (2018) tool to also include the measurement of a range of spatial and temporal scales. Fischer et al. (2021) applied a fitness-for-use approach to determine whether community science data is sufficient for specific end uses. Unlike the previous methods, the criteria used to measure data quality are predetermined. The user assigns each dataset a ranking for each criterion, and averages each criterion's rank to get a final, total rank of all datasets. Similar to the tool produced by Wentz and Shimizu (2018), this tool is designed for the comparison of multiple datasets representing the same feature, with the goal of selecting the ideal data for the user's needs.

2.3 EVALUATION OF EXISTING APPROACHES

Each of the above methods take a unique approach to quantifying spatial data quality. However, each have their drawbacks, as summarized in Table 2.1.

Table 2.1 Overview of relevant data quality assessment tools.

Study	Assessment output	Benefits	Challenges to application
Pôças et al. (2014)	Overall fitness value (%) for each dataset, calculated with matrices	Use of critical factors; suggested criteria are heavily adaptable to user's specific application	Requires dedicated metadata sheets provided with geospatial data layers (not always available); matrix calculations too complex
Wentz & Shimizu (2018)	Normalized score of data quality, calculated from score given to each criterion	Weighting of criteria; incorporates cost and benefit criteria; does not rely on metadata	Calculations are complex; only applicable when deciding between multiple available datasets for the same feature/phenomenon; subjective weighting has significant impact on final value
Fischer et al. (2021)	Overall score is average of rank value assigned to each criterion, criteria values are calculated using specific equations.	Incorporates range of spatial and temporal scales	Criteria and standards are predetermined so tool is less flexible; output value is a rank (relative to other data) so may be harder to use in decision making

As Pôças et al. (2014) note, their method analyzes metadata which is a) not always provided and b) when included, may not necessarily encompass all aspects of a dataset's quality. This reliance on metadata makes this method inadequate for the needs of this research.

One drawback of the method from Wentz & Shmizu (2018) is that it is designed for a user deciding between multiple datasets available to them. Often, a model producer only has one dataset available to represent a feature and this tool would therefore not be applicable. Importantly, the use of the multiple decision criteria matrix provides a detailed calculation of data quality but is a relatively difficult measure for individuals without advanced training in mathematics or spatial data to understand.

The tool produced by Fischer et al. (2021) uses a predetermined set of criteria. It is likely that some data users will have varying needs that are not accounted for in the predetermined criteria, potentially making this tool unapplicable. This prevents the tool from being applicable to diverse contexts. Further, the final ranking of each dataset provides the user information on the quality of each dataset relative to the others, but not necessarily an absolute value of data quality. In situations where only one dataset is available, the tool may not answer questions of fitness for use.

I was unable to find a method that meets all three criteria I specified (applicable to diverse model contexts and data types; does not rely solely on evaluating metatdata; can be simply communicated to stakeholders). I therefore chose to create a new, flexible tool to meet these specific criteria, using elements of each of the above methods.

2.4 DEVELOP NEW APPROACH TO ASSESS DATA QUALITY

To develop a novel approach which is friendly to users without advance geospatial analysis training, I chose to develop a mixed qualitative-quantitative binary calculator which can be tabulated manually or used in spreadsheet programs like Microsoft Excel.

Based on criteria used in the above examined examples, I chose eight criteria to evaluate data quality: positional accuracy/spatial resolution, timeliness, credibility, redundancy, lineage/transparency, spatial extent/geographical area, temporal extent/time period, and accessibility (described in further detail below). A dataset receives a score of one for each criterion for which it meets the required threshold, and a zero for any it does not. The user can decide that one or more criteria are not applicable to their research and omit them, thereby reducing the total possible score. It is possible to create a single equation to calculate a value for each dataset according to how many criteria and critical factors are met. However, the use of the table and the act of qualitatively describing how and why a criterion is or is not met encourages users to better understand the limitations of their model and its implication, so I encourage the use of the table rather than the development of an equation.

Though the criteria are predetermined, the standards for each criterion are assigned by the user according to the ontology of the analysis. For example, the user must determine whether the dataset meets an accuracy criterion (the closeness of the data observation to its actual position on Earth), but they themselves decide what is considered accurate (e.g., within 25 metres). One can select certain criteria to act as 'critical factors' (as introduced by Pôças et al., 2014), wherein a dataset should not be used in analysis unless each of the critical factor criteria are met. A user can also decide on a minimum total score necessary for a dataset to be considered in analysis.

The resulting approach to assess spatial data quality for use in ecological modelling and planning can be found in Table 2.2. The tool can either be used on a single dataset that represents one feature, or on all available datasets to represent that feature.

Table 2.2 Scoring table for evaluating the quality of geospatial data. User determines the standards for which to evaluate the criteria, as well as which, if any, criteria will be critical factors, based on the requirements of their analysis.

Criterion	Definition	Minimum standard	Critical factor? (yes/no)
Accessibility	Rights to access and use data		
Credibility	Reliability of the data collection, interpretation, and representation		
Timeliness	The degree to which the data represents the world at the relevant moment in time		
Lineage/ transparency	The trustworthiness of the dataset		
Positional accuracy/spatial resolution	The closeness of the data observation to its actual position on Earth		
Replication	The number of datasets available which provide representation for the indicator		
Spatial extent/geographical area	The spatial coverage (geographical area) of the dataset		
Temporal extent/time period	The time interval covered by the dataset		

2.4.1 Description of criteria

2.4.1.1 Accessibility

A key component of research being replicable is ensuring others have access to the same data (Xia, 2012). The accessibility criterion may require that data be open to others through open-source access or other data sharing agreements. In some instances, open access data is not the ideal; for example, when using data on species at risk or with culturally sensitive information. In such cases, the standard can be set to an appropriate level of accessibility (for example, available to researchers through private sharing agreements) or the criterion itself can be marked as not applicable.

2.4.1.2 Credibility

Credibility within a dataset is dependent on the degree to which it can be relied on to provide accurate information (Pratt & Madnick, 2008). This can be determined on the basis of an understanding of how the data was collected, interpreted and represented. One may examine whether standard protocols have been implemented, the producer is an expert in the field or key knowledge holder, or if an external review or audit was conducted. Author credibility or a study published in a peer-review journal may be used as a standard. For example, data provided by the federal government may be considered credible, however it is possible their data collection methods are not included in the metadata. The data would meet this credibility criterion but would fail the transparency criterion.

2.4.1.3 Timeliness

In order to meet the Timeliness criterion, data must have been produced within a time frame that is sufficient for the analysis in question. For present-day analyses, the criterion will be set to a time frame that reasonably captures modern phenomena. If the data represents historical conditions, then it must have either been collected at a time able to represent the condition sufficiently or produced using data collected within a reasonable interval around that time period. For example, data produced several decades ago may not be appropriate for a contemporary species distribution model but could be used as a baseline to guide restoration work.

2.4.1.4 Lineage/transparency

Lineage/transparency refers to the trustworthiness of the dataset (Yang et al., 2013). This can include an understanding of collection methods and analysis which provides the user greater knowledge of the dataset. Comprehensive metadata or other such communication may be required to meet this criterion. For example, protocol for a standardized data collection protocol provided along with a dataset, could be a standard for this criterion.

2.4.1.5 Positional accuracy/spatial resolution

The positional or spatial accuracy criteria examines whether the data accurately represents the phenomena in space (Yang et al., 2013). For a vector dataset (point, line, or polygon), positional accuracy represents the possible difference in distance between the actual objects and its representation in the dataset and may be two or three-dimensional. In the case of raster datasets, this criterion determines whether the resolution (cell size) is accurate. For example, a species distribution model for an animal that has a relatively small habitat range or niche requirement such as salamander may require finer spatial resolution than that for a large mammal. Positional accuracy is often dependent on the accuracy of the device with which data is collected.

2.4.1.6 Redundancy

Redundancy considers whether a phenomenon can be represented through multiple data sources, or only one. Generally, having more information to represent a phenomenon allows one greater flexibility in terms of how to model or analyse ecological patterns. For example, multiple datasets could be used to validate each other or extend the coverage of a feature.

2.4.1.7 Spatial extent/geographical area

A dataset must represent the phenomena of interest at a sufficient spatial extent for the analysis in order to meet this criterion (Xia, 2012). In other words, the data must be spatially representative of the entire applicable study area or distribution of the phenomena.

2.4.1.8 Temporal extent/time period

Temporal components of data are often overlooked (Estes et al., 2018). To meet this criterion, a dataset must represent the phenomena over a sufficient temporal scale. The timeliness criterion also considers temporal accuracy but considers whether the feature is recorded at a time considered representative of the actual occurrence. The temporal extent criterion applies when a range of time periods is required and examines whether the whole range is represented. There may be instances wherein this criterion is not applicable, for example if a study is looking at a plant species' distribution at one point in time. Whereas a bird life cycle model would involve a variety of spatial and seasonal ranges, and one may need data to represent the species across a temporal range.

2.5 CASE STUDY: ASSESSING DATA FOR USE IN BIOCULTURAL CONNECTIVITY MODEL

As a pilot study, I used this tool to assess and communicate the quality of spatial data available to represent species occurrences for modelling of biocultural connectivity in Unama'ki, as part of a research report prepared for the Unama'ki Institute of Natural Resources (UINR; Wall et al., 2022). Note that due to data-sharing agreements and contractual obligations, this report is not available to the public at the time of writing.

The purpose of this report was in response to a Request for Proposal from UINR to develop a plan for biocultural connectivity between Kluskap Cave (Cape Dauphin, Unama'ki) to the Bras d'Or Lake Biosphere Reserve (UINR, 2021). The research examined connectivity of four bioculturally significant species or groups of species as identified by Mi'kmaw knowledge holders. Spatial data to represent these features on the landscape in modelling were acquired from the Nova Scotia Forest Inventory (NS DNRR, 2021), the Atlantic Canada Conservation Data Center database (Churchill & Blaney, 2014) and the Global Biodiversity Information Facility database (GBIF; *Global Biodiversity Information Facility*, 2022; Figure 2.2). The NS Forest Inventory is a landcover dataset produced based on aerial imagery interpretations at a scale of 1:25,000 (NS DNRR, 2016). The ACCDC organize and collect data on biological diversity, particularly of species and ecosystems of conservation concern, for all of Nova Scotia, New Brunswick, Prince Edward Island and Newfoundland and Labrador (ACCDC, 2022). Lastly, GBIF is a global compilation of ecological data from a variety of sources, including museum collections, research and community science apps such as iNaturalist (*Global Biodiversity Information Facility*, 2022).

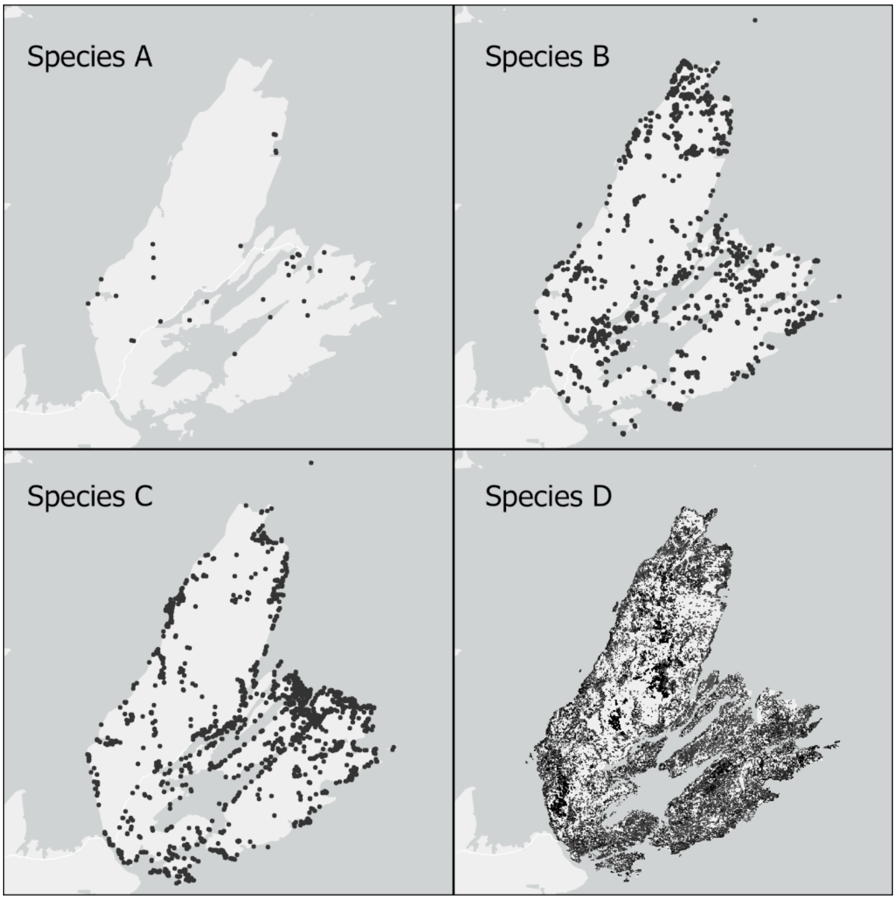

Figure 2.2 Spatial data representing distribution of bioculturally significant species, as used in case connectivity modelling project. Data for species A, B, and C were observational vector points, whereas data for species D was in vector polygon format and represents species composition.

To evaluate the quality of these data, I determined standards that they must meet in order to be considered fit for use (Table 2.3).

Table 2.3 Standards and explanations of assessment of data quality for data used in biocultural connectivity model.

Criterion	Definition	Minimum standard	Indicators that standard is met	Critical factor ?
Accessibility	Rights to access and use data	Publicly available or permission granted to be able to access/use	Agreements that allow for the data to be used in analysis and products from analysis can be delivered to partners and/or made public	Yes
Credibility	Reliability of the data collection, interpretation, and representation	Expert audit or review of data involved	Data collection protocol Is published in peer-review journal Metadata indicate standards of practices for community science (i.e., what constitutes research grade) Expert is considered a key knowledge holder in their community	No
Timeliness	Degree to which the data represents the world at the relevant moment in time	5 years for species A, B and C 10 years for species D	Metadata provides data collection time periods Collection dates are included in data itself	No

Criterion	Definition	Minimum standard	Indicators that standard is met	Critical factor ?
Lineage/ transparency	The trustworthiness of the dataset	Description of data production methods is available	Metadata are available which describe the process of data collection or production Standards of practice for community science are given	No
Positional accuracy/spatial resolution	The closeness of the data observation to its actual position on Earth	Within 25 m	Raster: Resolution at least 25 m^2 Vector: Minimum Mappable Unit 25 m or less Point Data: Accuracy of 25 m or less	No
Redundancy	Number of datasets available to represent indicator	Some level of redundancy	More than one dataset is available to represent each species of interest	No
Spatial extent/geographical area	The spatial coverage of the dataset	Covers applicable study area and/or indicator range	Spatial extent meets or exceeds the study area	Yes
Temporal extent/time period	The time interval covered by the dataset	Available across all dates and year ranges for which the feature is relevant	Metadata provides data collection time periods Collection dates are included in data itself	No

The resulting assessment can be found in Table 2.4. Note that the scores obtained here for the ACCDC and GBIF data are dependent on the species chosen for analysis and do not reflect that of the entire database or of other individual species data.

Table 2.4 Data quality score for each dataset included in case study analysis, according to user-defined standards. Criterion designated critical factors are italicized.

Criterion	**ACCDC**			**GBIF**			**NS Forest Inventory**
	Species A	**Species B**	**Species C**	**Species A**	**Species B**	**Species C**	**Species D**
Accessibility	1	1	1	1	1	1	1
Credibility	1	1	1	1	1	1	1
Timeliness	1	1	1	1	1	1	0
Lineage/ transparency	0	0	0	0	0	0	1
Positional accuracy/spatial resolution	0	0	0	1	1	1	1
Redundancy	1	1	1	1	1	1	0
Spatial extent/geographical area	1	1	1	1	1	1	1
Temporal extent/time period	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Total score	5	5	5	6	6	6	5

The analysis was conducted on the datasets available for each feature individually. However, the ACCDC and GBIF datasets scored consistently between each feature, and so the results are described for the datasets as a whole below.

Based on the standards set, the NS Forest Inventory dataset does not meet the timeliness or redundancy criteria. The photography which the NS Forest Inventory data is based on was taken as early as 2008 and 2009 and therefore is not considered current (defined as within 10 years for Species D), despite being downloaded from the provincial website in 2021 (NS DNRR, 2021). The timeliness standard of 10 years was chosen because although an untouched forest stand may not change in that period, those undergoing silvicultural management or subject to natural disturbance could change drastically. Additionally, there are no other data which describe the distribution of species D in Nova Scotia that could replace the NS Forest Inventory and therefore it does not meet the redundancy criterion.

The ACCDC dataset does not provide information on the positional accuracy of all observations and does not meet the first criterion. Though some datasets withhold positional accuracy information to conceal exact locations of sensitive species, the species included in this analysis were not considered at-risk and thus the lack of positional accuracy information can not be attributed to their protection. The ACCDC dataset is a compilation of observations from various projects that used differing methodologies that are not clearly communicated and so does not meet the lineage criterion.

Finally, the observations included in GBIF are collected by community scientists and are not considered collected using a standard methodology, so the dataset does not meet the lineage criterion.

It is worth noting that both the ACCDC and GBIF datasets contain information collected more than 5 years ago, which was the standard for the timeliness criterion. However, there were sufficient data collected within the 5-year period that allowed these datasets to meet that criterion. With this information, one could choose to either remove data collected outside the desired timeframe, or as was the case in this project, include the older data with the understanding that the relevant time period is nonetheless represented.

All datasets met the two critical factor criteria, accessibility and spatial extent. However, none of the three datasets included in this case study met every criterion included in the quality scoring table. While it is ideal to employ data which meet every criterion, we are limited to the data available to us. As in the case with this project, a dataset which does not receive a perfect score, so long as all critical factors are met, can still be included in analysis so long as the results are interpreted cautiously.

2.6 APPLICATIONS OF NOVEL APPROACH

The case study model of biocultural connectivity was produced as part of an unpublished report (Wall et al., 2022). The data quality assessment tool was used to communicate uncertainty to the contracting organization, and to contextualize results of the model. The evaluation tool itself highlighted what aspects of the data are low quality. For example, the fact that neither the ACCDC nor GBIF datasets, which represented 3 of the 4 species selected, met the lineage/transparency criterion is worth noting. Recommendations in this report included further ground truthing and validation, through surveys and camera traps, to collect more reliable data. In addition, available data for species A is sparse (Figure 2.2), despite the species range and habitat requirements indicating it should be more present throughout the study area. Focused data collection for that species was recommended.

Use of this tool benefits both the data user or model producer, as well as partners or stakeholders. For the model producer, the score a dataset receives can be used to inform several decisions. A low score may indicate low quality, and the user may deem the data unfit. If two datasets are available to represent the same feature (and it is not sensible or not possible to combine them), the scores of each can be compared to determine which is of higher quality or which should be included in analysis. If it is found that no high-quality dataset is available to represent a certain feature, this tool can aid users in deciding whether to continue with modelling based on available data, and future data collection efforts could be focused to fill that gap. In addition, partners not involved in the creation of models can use the output of this assessment to base their decisions on a rooted understanding of the ways the input data may be influencing the model.

2.7 CONCLUSION

Similar to the decision making framework from Wentz and Shimizu (2018) the tool proposed here also does not rely solely on the use of metadata, as is the case for the method proposed by (Pôças et al., 2014). Unlike Wentz and Shimizu (2018), however, I decided against using multiple criteria decision making (MCDM) and individual quality formula to maintain simplicity. A simple binary approach to assessing data quality, as proposed here, streamlines data inclusion and cleaning decisions, making it more appealing to model builders to assess and communicate data quality. In addition, though a formula could be created for the presented tool, displaying the table to partners encourages a better understanding of which criteria and or critical factors were and were not met. Importantly, a simpler tool is more accessible to those not involved in the production of spatial data and ecological models. Removing complex calculations reduces barriers to understanding of data quality by potential stakeholders, such as policy makers, communities or other researchers who may not have expertise in mathematics or spatial data quality. Therefore, these groups are more able to use, understand and critically analyze model outputs, as based on this understanding of the input data.

While we often have little control over the availability and quality of spatial data, this tool provides a straightforward, standardized approach to transparent decision-making regarding the use of data. The assessment here can provide users information on necessary data cleaning, can allow one to continue with building an ecological model with confidence, or makes one aware of uncertainties in their model that they can then easily communicate to partners.

CHAPTER 3 ANALYSIS OF BOREAL FOREST LOSS AND CHANGE IN CONNECTIVITY TO GUIDE RESTORATION EFFORTS IN UNAMA'KI

3.1 INTRODUCTION

Boreal forests make up 27% of the world's forest area (FAO, 2020) and are Canada's largest biome. Limited to northern circumpolar regions, boreal forests are dominated by species within the *Abies, Larix, Picea, Pinus, Populus* and *Betula* genera (Brandt, 2009) and succession dynamics are influenced by fire, insects and disease (Brandt et al., 2013). Boreal forests provide vital services including water regulation and filtration, carbon sequestration and storing, erosion control, habitat, nutrient cycling, cultural and recreational opportunities, and materials, to name a few (Anielski & Wilson, 2005). The boreal forest biome is under increasing stress due to warming temperatures (Henry, 2005), non-native species (Langor et al., 2014) and particularly human resource extraction and development (Gauthier et al., 2015; Kreutzweiser et al., 2013; Schindler & Lee, 2010).

Unama'ki is one of seven districts in Mi'kma'ki and is governed by the Peace and Friendship treaties. These treaties did not cede or surrender Mi'kmaq rights to the land but in fact stated Mi'kmaw rights to hunt, fish and earn a moderate livelihood from the land and resources which they have stewarded since time immemorial (Treaty or Articles of Peace and Friendship 1752, 2008). Unama'ki contains 77 protected areas, including Cape Breton Highlands National Park, which in total cover about 33% of the total landmass. The Unama'ki Institute of Natural Resources has also helped established the Sepite'tmnej Kmitkinu Conservancy which, alongside other Mi'kmaq Nations, are in the process of establishing Indigenous Protected and Conserved Areas (IPCAs).

Unama'ki contains the only boreal forest found in Nova Scotia, which provides habitat for a number of species at risk, including the federally-listed Bicknell's thrush (COSEWIC, 2009), and provincially-listed Canada lynx and American marten

(Endangered Species Act, 1998; Latourelle & Bird, 2010). Succession of boreal forest in Unama'ki is naturally controlled by spruce budworm (*Choristoneura fumiferana* (Clemens); SBW) outbreaks (Baskerville, 1975) which defoliate and kill predominantly balsam fir and white spruce trees every 30 to 40 years (Boulanger & Arseneault, 2004; Government of Canada, 2013; Royama et al., 2005). The most recent large outbreak of spruce budworm began in 1974 (Ostaff & MacLean, 1989) and continued until populations crashed in 1982. Balsam fir mortality ranged from 73 to 86% between 1976 and 1985 (MacLean & Ostaff, 1989). Following the outbreak, moose (*Alces andersonii,* (Peterson)) began browsing on the regenerating saplings.

It is important to note here that the subspecies of moose native to Unama'ki, *Alces alces americana* (Clinton)*,* or Eastern moose, was believed to have been extirpated sometime in the 1920s to 1930s (Bridgland et al., 2007). It is likely the population suffered from disease (Browne & Derek, 1996) and was hunted to extirpation (Bridgland et al., 2007), despite the Mi'kmaq having sustainably harvested eastern moose in Unama'ki for thousands of years prior to European colonization. Cape Breton Highlands National Park (henceforth the Park or CBHNP) introduced 18 Western moose (*Alces alces andersonii*) into the Park in 1947 and 1948 (Lothian, 1976), descendants of which have persisted in the region to present day. The western and eastern moose subspecies fill similar ecological niches, however the historical context is worth noting. With no natural predators and an increase in saplings following the SBW outbreak, moose populations in Cape Breton Highlands National Park grew from an estimated 215 individuals in 1977, to 1,126 in 1985 (as reported in Bridgland et al., 2007). A density of 1 moose per square kilometer is the threshold where the Park considers the population transitions from Good to Fair conditions, according to their Ecological Integrity Monitoring Program (R. Smith et al., 2015). Moose abundance reached a high of 4.2 moose/km^2 in 2004, and dropped below 2.0 moose/km^2 in 2006 (R. Smith et al., 2015). The population has remained consistently above the 1 moose/km^2 threshold as of 2015 (R. Smith et al., 2015). Their hyperabundant population led to over-browsing of stands regenerating after the SBW outbreak, causing many areas to convert to grasslands (C. Smith et al., 2010).

In addition to moose browse, large tracts of boreal forest impacted by the SBW outbreak outside of protected areas were salvage logged to minimize lost profits (Nova Scotia Department of Natural Resources, 1994). The loss of boreal forest limited the services provided by intact boreal forest cover, but also led to a decrease in boreal-dependent species including Bicknell's thrush (D'Orsay & Howey, 2020). Boreal forest in Unama'ki has been reduced in area now considered fragmented. Fragmentation is the breaking up of contiguous habitat into isolated patches (Haddad et al., 2015). Ecological connectivity, on the other hand, is a measure of the extent to which a landscape supports the movement of organisms and ecological processes within and between patches of suitable habitat (Taylor et al., 1993).

3.1.1 Defining ecological connectivity

Broadly speaking, ecological connectivity is a key component of any sustainable ecosystem and is necessary in both freshwater and terrestrial habitats, though terrestrial forest connectivity will be the focus of this study. Watson et al. (2018) summarize the increasing importance of intact and connected forest ecosystems to climate regulation, watershed services, biodiversity, Indigenous peoples and human health. In Unama'ki, the connectivity of boreal forest would naturally have fluctuated through time due to natural succession patterns (predominantly spruce budworm) maintaining mixed age stands. In addition, contiguous boreal forest would be naturally disrupted by hardwood dominant forest along steep valley slopes (Latourelle & Bird, 2010). Unama'ki is also an island, making forest connectivity naturally constricted by a relatively small total area for seeds to disperse, compared to mainland Canada.

Landscapes can be naturally fragmented due to topography, waterways, etc., however the abrupt fragmentation of a previously connected landscape can have myriad impacts. As contiguous patches of habitat become fragmented, areas previously found in the inner portions of the habitat may now be exposed to the edge, and forced to interact with other matrix habitat types (Benitez-Malvido & Arroyo-Rodríguez, 2008; Fonseca, 2008). This is known as the edge effect, which can alter microclimate conditions and have negative implications for species dependent on interior habitat (Moen & Jonsson, 2003). At the landscape scale, several migratory species, including some birds (Haas, 1995) and ungulates (Bolger et al., 2008; Greenaway, 2016), require contiguous habitat to survive migration, and long distance travel may be impeded by fragmented landscapes. The maintenance of viable populations is greatly dependent on resource accessibility; if resources become isolated in separate habitat patches, they are more likely to become scarce (Fahrig & Paloheimo, 1988; Saunders & Ingram, 1987). Further, anthropogenic climate change is causing rapid shifts in many species' ranges (Davis & Shaw, 2001), and their ability to locate and move to viable habitat will be determined by the connectivity of the landscape through which they must navigate (Krosby et al., 2010).

Western science generally recognizes two key components of ecological connectivity. The first, structural connectivity, is assessed based on the physical extent and contiguity of landscape features such as forest cover, geology, and elevation (Rudnick et al., 2012). The second, functional connectivity, is assessed based on the response of organisms and ecological processes to the configuration of these various elements in a landscape. Functional connectivity represents the extent an organism will use and move through the landscape's vegetation cover and elevations (Crooks & Sanjaran, 2006). Structural connectivity can be relatively easy to quantify spatially, so long as there is an accepted definition of, and sufficient data available to represent, the landscape features of interest. For example, an area of contiguous grasslands would be considered structurally connected. Functional connectivity, on the other hand, requires the researcher also understand and quantify details about the species of interest (Schneider, 2019), including habitat preference, distribution, predator avoidance behaviour and other items related to natural history, to determine what landscape elements that organism can move through and at what part of their life cycle. To continue the example, an organism that requires grasslands at one part of their life cycle and forest cover at another, will require connectivity of grasslands and forests to survive.

3.1.2 Protected area management and connectivity modelling

The Canada National Parks Act (2000), which governs National Park management, states that the "maintenance or restoration of ecological integrity […] shall be the first priority of the Minister when considering all aspects of the management of parks." Wherein ecological integrity is defined as "a condition that is determined to be characteristic of its natural region and likely to persist, including abiotic components and the composition and abundance of native species and biological communities, rates of change and supporting processes" (Canada National Parks Act, 2000). Required by law to engage in restoration of ecological integrity, Cape Breton Highlands National Park has responded to the loss of boreal forest within the Park through the Bring Back the Boreal campaign. The Park organized a moose harvest conducted by the Mi'kmaq in partnership with the Unama'ki Institute of Natural Resources (UINR) in 2015 – 2018 (D'Orsay & Howey, 2020). In addition, moose exclosures were built in areas of intense browsing (D'Orsay & Howey, 2020). The goal of these measures was to minimize further moose browse and determine effect of moose browse. However, it is possible that areas converted to grasslands have reached a new stable ecological state and may not revert to boreal forest cover unless more proactive measures are taken (C. Smith et al., 2010).

Parks Canada is therefore beginning a tree planting program to increase the number of balsam fir and white spruce saplings and expedite boreal forest regeneration (D'Orsay & Howey, 2020). The tree planting efforts support the federal government's goal to plant 2 billion trees in Canada (2020). Finite resource capacity limits the Park's ability to reforest all areas that have lost boreal forest cover. Due to the increased benefits of intact, connected forests, the Park is interested in strategically planting trees to restore forest connectivity. An understanding of the connectivity of the forest landscape is therefore required.

Models of landscape connectivity are commonly used to guide systematic conservation and restoration management (Galpern et al., 2011; Rudnick et al., 2012; Stewart-Koster et al., 2015). Several software programs and algorithms exist to model ecological connectivity, however the one most applicable to the present management goal of prioritizing areas for forest connectivity restoration is Zonation (Moilanen, 2014). Zonation is a spatial prioritization software that iteratively assigns cells a value between 0 and 1 according to habitat quality and can incorporate several parameters including connectivity. Zonation's ability to prioritize areas for connectivity is often used in planning contexts such as to guide sustainable forestry (Westwood, Lambert, et al., 2020), protected area planning (Albert et al., 2017; Lehtomäki et al., 2009) and conservation monitoring (Carroll et al., 2010).

3.1.3 Research objectives

The objectives of this research are to: 1) quantify historical forest loss and assess the significance of that loss and associated fragmentation of forest patches; 2) apply a spatial prioritization algorithm to identify forest stands that were historically structurally connected and to 3) guide restoration efforts through prioritization of stands for tree planting based on historical connectivity. The objectives can be broken down into three research questions:

1) How has coniferous forest cover changed between 1972, 1989, 1999, 2009 and 2019?
2) How connected was the coniferous forest landscape in 1972, 1989, 1999, 2009 and 2019, and how has it changed over time?
3) Where should tree planting efforts be prioritized to restore forest in areas of high connectivity prior to the SBW outbreak?

The analysis incorporates forest cover data over several time steps, including prior to the spruce budworm outbreak (1972) on to present day conditions (2019). This work presents the first examination of change in forest composition and connectivity in Unama'ki, and the first known application of Zonation to guide treeplanting and restoration efforts using historical connectivity.

3.2 METHODS

The study area includes the northwestern arm of Unama'ki (Figure 3.1). The retreat of the Wisconsin glacier around 10,000 years ago left glacial deposits which largely influence modern day topography (Browne & Derek, 1996). Between 1981 and 2019, the weather station in Cheticamp located just southwest of Cape Breton Highlands National Park, measured an annual mean temperature of 6.4 °C, ranging from -4.9 °C in January to 18.3 °C in July, and an annual total precipitation of 1,375.1 mm, with mean precipitation of 142.9 mm in January and 90 mm in July (ECCC, 2013). Unama'ki island contains several ecoregions: Northern Plateau, Cape Breton Highlands, Nova Scotia Uplands, Northumberland/Bras d'Or, and Atlantic Coastal (Neily et al., 2017). Within the study area (Figure 3.1), Eco districts 100 – Northern Plateau, 210 – Cape Breton Highlands, 220 – Victoria Lowlands, 310 Cape Breton Hills, 320 – Inverness Lowlands and 510 – Bras d'Or Lowlands are all present (Neily et al., 2017). The three main vegetation types that make up Cape Breton Highlands National Park include boreal forest, Acadian forest (mix of hardwoods and softwoods) and taiga (Parks Canada Agency, 2018). The boreal forest region is dominated by balsam fir, white spruce, black spruce (*Picea mariana* (Mill.) Britton, Sterns & Poggenburg), white birch (*Betula papyrifera* (Marshall)) and American mountain ash (*Sorbus americana* (Marshall)).

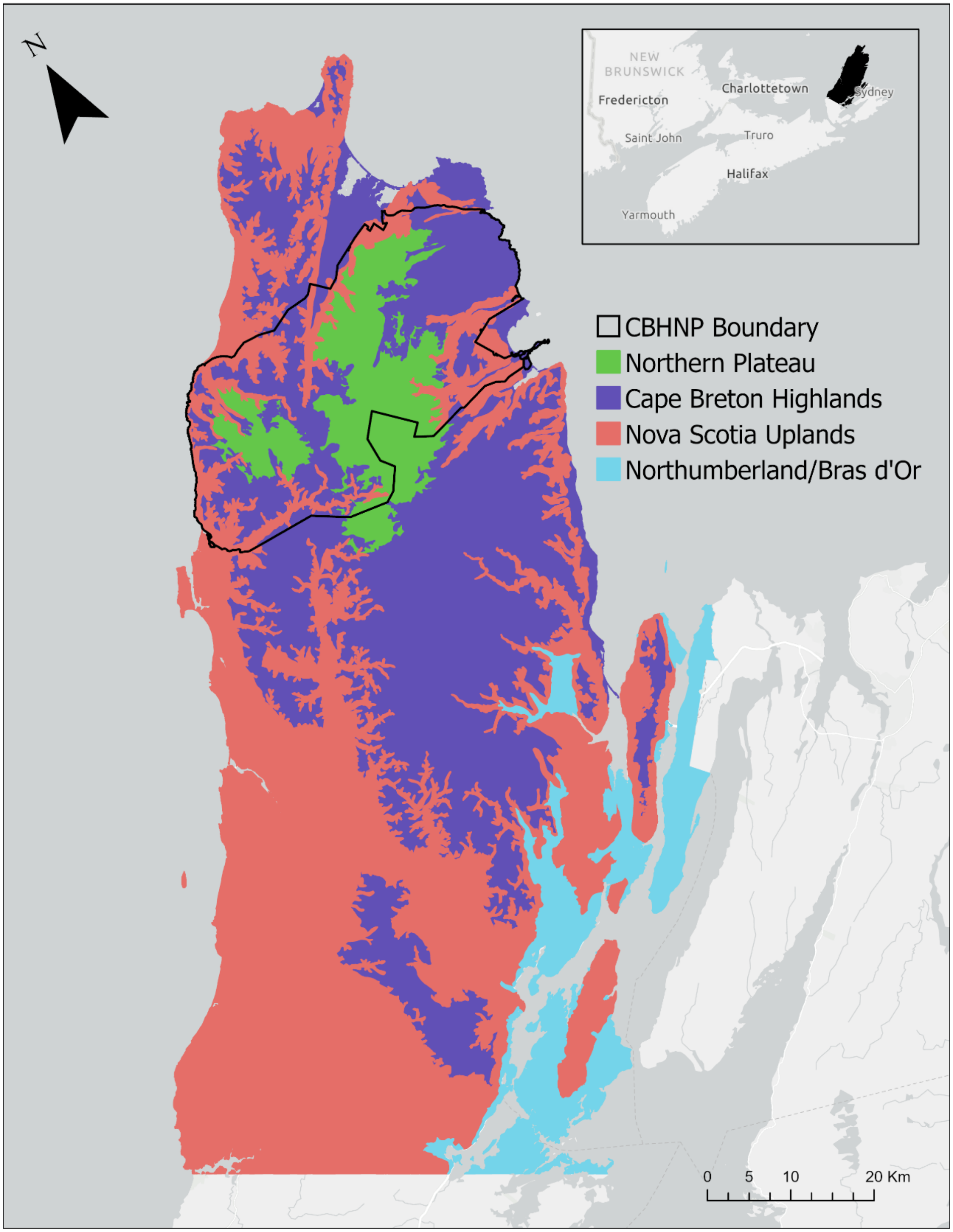

Figure 3.1 Ecoregions present in study are shown with Cape Breton Highlands National Park (CBHNP) indicated by black border. Inset map shows study area within the context of Nova Scotia.

3.2.1 Description of spatial data

Forest cover data across multiple years was provided by Parks Canada staff using Landsat imagery (A. Moody, personal communication, October 24, 2021). See Figure 3.2. In 2021, Parks Canada staff created forest cover raster layers from Landsat 1, 4, 5, 7 and 8, imagery at 30 m resolution. The R package LandsatLinkr was used to calibrate imagery between years. The entire spatial extent of this dataset was used as the boundary for this study. The data were projected at Lambert Conformal Conic (2SP) and divided into four forest types: 'coniferous', 'deciduous', 'disturbed', and 'mixed' forest; it is available for the years 1972, 1989, 1999, 2009 and 2019 (Figure 3.2). At the time of writing the data have only been validated within Cape Breton Highlands National Park. To do this, Park staff compared the forest cover layers with aerial photos from 1973, 2009 and 2019 to determine whether the layers accurately differentiated between forest gain, forest loss and no change areas (M. Lemieux, personal communication, August 1, 2023). All layers differentiated between these categories at a success rate of 75%. As Copass et al. (2019) note, office based validation methods such as this can be as reliable as in field validation methods. In general, however, it is likely the 1972 layer is less accurate than the subsequent time step layers, because the satellite technology available from 1985 onwards (Landsat 5 and onwards) showed better performance.

The 'disturbed' forest type consists of forest that has been lost due to abrupt changes such as logging and the spruce budworm outbreak. Grasslands produced as a result of moose browse are included in this disturbed class. Throughout the study, 'forest stands' are an often-used metric. [A stand is considered a group of adjacent cells (4 nearest neighbours) that contain the same forest cover type.] As the most recently collected data, the 2019 dataset is used as a proxy for present day forest conditions.

The Landsat satellite imagery which this data is based on is widely used in spatial analyses (Wulder et al., 2022). However, as far as can be understood from the literature, the imagery was captured without the prior informed consent of the Mi'kmaq, the ancestral stewards of Unama'ki. Providing free, prior informed consent is a core principle in the United Nations Declaration on the Rights of Indigenous Peoples (UNDRIP; United Nations, 2008) and OCAP® (Ownership, Control, Access and Possession) principles (The First Nations Information Governance Centre, 2014). I acknowledge that this issue is persistent in satellite imagery and remote sensing analyses, as well as my own limitation to address this issue as it is outside the scope of this thesis.

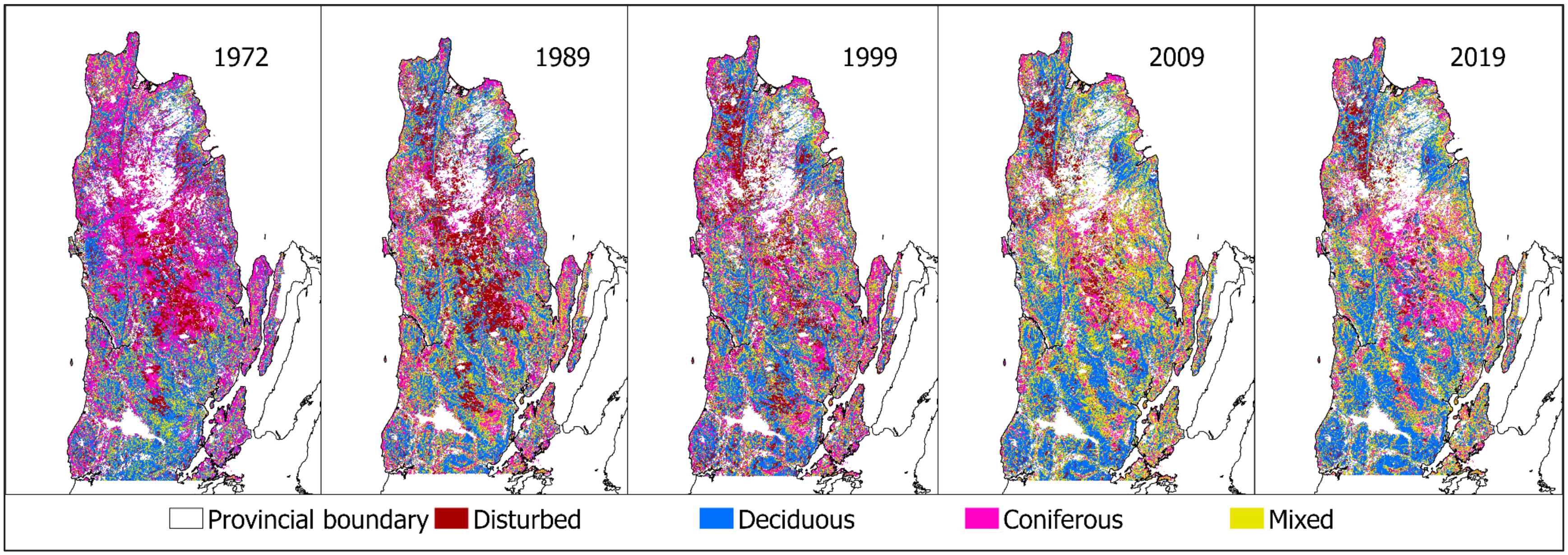

Figure 3.2 Forest cover data provided by Parks Canada at 30 m resolution for all forest types at each time step.

In addition, a layer representing areas of non-forest was produced using the Nova Scotia Forest Inventory, as downloaded in December 2021. All areas containing the FORNON fields 70 through 78, 84 through 87, 91 – 95, 97, 98, and 99 were included (NS DNRR, 2016). This non-forest layer represents lakes, roads and other non forest features (see Appendix A for full description of these fields). There is no spatial overlap between the non-forest layer and any of the forest cover data provided by Parks Canada. The data were converted to raster format at 30 m resolution for use in Zonation. Finally, protected areas boundary data was downloaded from the Nova Scotia Open Data Portal in December 2021. This layer includes national parks, national wildlife areas, provincial wilderness areas, provincial nature reserves, selected provincial parks and selected land trust properties and easements (NS ECC, 2021). Both data were projected to Lambert Conformal Conic (2SP). The protected areas layer was not used in any connectivity models but was incorporated in the final examination of model results. A summary of all data used can be found below Table 3.1.

Table 3.1 Summary of spatial data used in analysis.

Name	Description	Data type	Date produced	Date downloaded	Source
Forest cover	Contains four forest types: coniferous, deciduous, disturbed, and mixed; available for the years 1972, 1989, 1999, 2009 and 2019	Raster, 30 m	2021	October, 2021	Cape Breton Highlands National Park
Nova Scotia Forest Inventory	Forest inventory of NS, interpreted from aerial photography	Vector, polygons, 25 m MMU	2008-2009*	December, 2021	NS DNRR (2021)
Nova Scotia Protected Areas	Includes National Parks, National Wildlife Areas, Provincial Wilderness Areas, Provincial Nature Reserves, selected Provincial Parks and selected land trust properties and easements	Vector, polygons	2020, updated continuously	December, 2021	NS ECC (2020)

*Some data in entire forest inventory is older, this date is inclusive of only data that falls within the study area.

3.2.2 Assessment of data quality

Ecological models, such as the connectivity analysis in this study, attempt to describe or predict patterns in nature. In ideal scenarios, model builders have accurate, extensive data to represent ecological features and phenomena as they occur in the real world. However, there is inevitably error, inaccuracies and misrepresentations within the data upon which these models are built, potentially creating unreliable results (Aerts et al., 2003). These issues are persistent in ecological modelling, and yet models are built and decisions made based on them regardless. While remedying uncertainty in the data used in this present analysis is outside the scope of this research, it is nonetheless necessary to quantify and communicate them to readers. Transparent communication of error ensures the reader and stakeholders are able to use these results properly and make informed decisions about their use (Prager et al., 2018).

In Chapter 2, I introduced a tool to efficiently quantify and communicate the uncertainty of spatial data used in ecological modelling (Table 2.2). The table outlines several criteria which an ideal dataset would meet. Inevitably not every criterion will be met by a dataset, but highlighting which are and which are not informs the ways that a dataset may be introducing uncertainty to a model. A dataset is given a score of '1' for every criterion it meets and a '0' for each it does not, for a potential total score of 8. Individual criterion can be designated critical factors, which must be met in order for the data to be fit for use.

I defined standards for each criterion to evaluate the quality of forest cover data at each time step, as well as the non-forest data, for use in connectivity and treeplanting prioritization modelling (Table 3.2). The protected areas data was not used as an input to any model, but used to analyze model outputs, so was not included in this assessment. Spatial and temporal extent were both considered critical factors.

Table 3.2 Standards and explanations of assessment of data quality for data used in models of forest connectivity and tree planting prioritization.

Criterion	Definition	Minimum standard	Indicators that standard is met	Critical factor ?
Accessibility	Rights to access and use data	Publicly available or permission granted to be able to access/use	Agreements that allow for the data to be used in analysis and products from analysis can be delivered to partners and/or made public	No
Credibility	Reliability of the data collection, interpretation, and representation	Expert audit or review of data involved	Data collection protocol	No
			Is published in peer-review journal	
			Metadata indicate standards of practices	
			Expert is considered a key knowledge holder in their community	
Timeliness	Degree to which the data represents the world at the relevant moment in time	Represents conditions for corresponding time steps	Metadata provides data collection time periods	No
			Collection dates are included in data itself	
Lineage/ transparency	The trustworthiness of the dataset	Description of data production methods is available	Metadata are available which describe the process of data collection or production	No

Criterion	Definition	Minimum standard	Indicators that standard is met	Critical factor ?
Positional accuracy/spatial resolution	The closeness of the data observation to its actual position on Earth	Within 25 m	Raster: Resolution at least 25 m^2 Vector: Minimum Mappable Unit 25 m or less Point Data: Accuracy of 25 m or less	No
Redundancy	Number of datasets available to represent indicator	Some level of redundancy	More than one dataset is available to represent each species of interest	No
patial xtent/geographical rea	The spatial coverage of the dataset	Covers applicable study area	Spatial extent meets or exceeds the study area	Yes
emporal extent/time period	The time interval covered by the dataset	Available across year ranges for which the feature is relevant	Metadata provides data collection time periods Collection dates are included in data itself	Yes

The forest cover data provided by Parks Canada met 6 of the 8 criteria, while the non-forest data from the NS Forest inventory met 5 out of 8 (Table 3.3). Both datasets were deemed acceptable for use.

Table 3.3. Quantifying quality of forest cover data provided by Parks Canada available for each time step (1972, 1989, 1999, 2009, and 2019) and the non-forest data acquired from the NS Forest Inventory. Criteria designated critical factors are italicized.

Criterion	**1972**	**1989**	**1999**	**2009**	**2019**	**Non-forest**
Accessibility	1	1	1	1	1	1
Credibility	1	1	1	1	1	1
Timeliness	1	1	1	1	1	0
Lineage/ transparency	1	1	1	1	1	1
Positional accuracy/spatial resolution	0	0	0	0	0	1
Redundancy	0	0	0	0	0	0
Spatial extent/geographical area	1	1	1	1	1	1
Temporal extent/time period	1	1	1	1	1	N/A
Total score	6	6	6	6	6	5

At 30 m resolution, the forest cover data does not meet the standard for high positional accuracy. That said, the data is the only known forest cover data at such high resolution for the year 1972 in this area. Therefore, while it may not be considered as accurate as some present-day spatial data, it is certainly relatively accurate compared to what is available historically in this region. Furthermore, there is no other data available to represent forest cover at these time steps, so the data do not meet the redundancy criterion.

The non-forest dataset did not meet the timeliness or redundancy criteria. The imagery which the NS Forest Inventory data is based on was taken as early as 2008 and 2009 and therefore is not considered current, despite being downloaded from the provincial website in 2021 (NS DNRR, 2021). However, there are no other data which describe the non-forest cover in Nova Scotia with this accuracy, and thus I will proceed modelling with this layer while being aware of its temporal limitations.

3.2.3 Quantifying coniferous forest loss over time

ArcGIS Pro version 2.7.3 (2020a) and IBM SPSS Statistics software version 28.0.1.1 (2023) were used to determine the amount and location of forest loss that occurred between 1972, 1989, 1999, 2009 and 2019. The coniferous forest cover data is of particular interest due to the preferential selection of spruce budworm, and subsequent higher impact, to coniferous species. I calculated total coniferous forest loss between adjacent time steps and between the base time step (1972) and all subsequent time steps. In addition, I calculated the percent change in coniferous forest cover within and outside protected areas.

Next, I measured three coniferous forest structure characteristics for each time step: 1) mean stand area, 2) mean stand perimeter and 3) mean stand normalized perimeter index in ArcGIS Pro. Mean values for each of these measurements were then calculated in IBM SPSS. While forest stand area and perimeter were used to better understand the change in forest cover over time, neither are direct indications of the *configuration* of forest change. It is possible that despite forest area and perimeter increasing between time steps, the stands themselves may have converted to more convoluted shapes which does not necessarily increase connectivity. A measure of compactness referred to here as a normalized perimeter index (NPI) was used to account for this (Reock, 1961):

$$NPI = \frac{2 \times \sqrt{\pi \times area}}{perimeter}$$

Where an NPI value closer to 1 indicates a more compact shape, with '1' being the NPI for a circle.

A statistical analysis of change in average forest patch size (area), perimeter and normalized perimeter index between time steps was conducted through a one-way ANOVA (Ross, 2017) in IBM SPSS (*IBM SPSS Statistics*, 2023). Post hoc analyses using Tukey HSD and Bonferroni tests were also conducted (Ross, 2017).

ArcGIS Pro was then used to create visualizations of forest change spatially between all years found to have a significantly different mean stand area and perimeter. The raster calculator function was used to determine whether cells converted to coniferous forest (gain), away from coniferous forest (loss), or did not change (no change) between time steps.

Next, a grid of hexagonal cells with an area of 1 km^2 was created for the entire study area. Using spatial statistics in ArcGIS Pro, four coniferous forest cover characteristics were measured per square kilometer hexagonal grid cell at each time step: 1) average patch size; 2) average patch perimeter; 3) total forest area; and 4) total forest perimeter.

3.2.4 Zonation prioritization analyses

I conducted an analysis of structural connectivity of coniferous forest using Zonation software, version 4.0.0 (Moilanen, 2014). Zonation analyzes raster data on selected features in a study area, such as species occurrences, distribution data, habitat, anthropogenic disturbance, and any other features of interest. These features can be assigned varying positive or negative weights. The algorithm systematically ranks each cell according to its value to both habitat quality and connectivity and to the weight of features present in each raster cell (Lehtomäki & Moilanen, 2013). Greater abundance of high value features indicates higher habitat quality. The program works by first removing cells that have lower value, as determined by parameters set by the user, while also maintaining habitat quality and connectivity. It continues to do this, removing the least important cells, until all cells have been ranked. The cells removed towards the end of this process are of highest value, according to the parameters and weights set by the user.

The order in which cells are removed is determined by the cell removal rule. The three main removal rules include target-based planning, additive benefit function (ABF), and core-area Zonation (CAZ) (Moilanen et al., 2012). I used the CAZ removal rule. Target-based planning requires the user pre-determine a proportion of the landscape to be prioritized. ABF prioritizes areas with high densities of highly weight features, regardless of the distribution or abundance of features on the landscape. Finally, CAZ prioritizes areas that contain rare, positively weighted features. CAZ first removes cells that have common and low-weighted features. After a cell is removed, the software recalculates the distribution of all features and again removes those with few occurrences of common features. Eventually, features that were once common become rare and are then prioritized so that cells containing other, now common, features are removed. CAZ works to maintain as many occurrences as possible of rare and high-weighted features across the landscape and may therefore prioritize areas that have low density of feature occurrences but contain important features. In order to ensure all features were maintained throughout the analysis, I used the CAZ removal rule.

Zonation contains several optional settings and can be used to build impressively complex ecological models. The structural connectivity models in my research are relatively simple and use one key parameter in Zonation called *distribution smoothing*. Distribution smoothing essentially smooths the value of a cell to neighbouring cells, up to a distance set by the user (Moilanen et al., 2012). This distance is the dispersal kernel or the landscape use of the feature, such as home range or seed dispersal. The dispersal kernel is specific to each feature. Zonation uses an alpha value to calculate distribution smoothing:

$$\alpha = \left(\frac{2}{[dispersal\ kernel]}\right)$$

Features on the landscape that occur within this distance are considered connected and given higher value than those which are isolated (Moilanen et al., 2012).

Determination of feature-specific dispersal kernels requires an understanding of a species' habitat use characteristics. Because the data used in this model is classified at the forest type level, an exact dispersal kernel at the species level is impossible to define. An examination of the habitat use and dispersal of key species in boreal forest (Table 3.4) can be used to better understand habitat range patterns in the area.

Table 3.4 Seed dispersal estimates for key tree species and habitat ranges for species associated with boreal forest habitat in Unama'ki.

Species	Habitat range/seed dispersal	Source
Black spruce (*Picea mariana*)	~ 80 m	Fryer (2014)
Balsam fir (*Abies balsamea*)	25 – 60 m	Frank (1990)
American marten (*Martes americana*)	600,000 – 20,560,000 m^2	Buskirk & McDonald (1989)
Bicknell's thrush (*Catharus bicknelli*)	184,000 m^2	Ward (2020)
Canada lynx (*Lynx canadensis*)	12,000 – 32,000 m^2	Parker et al. (1983)

Seed dispersal and habitat ranges vary significantly by species (Table 3.4). Four pilot models were developed at dispersal kernels of 80 m, 500 m, 1000 m, and 2000 m using the 1972 coniferous forest data. Mapped outputs of each pilot model showed similar visual clusters of the most highly prioritized areas. Visualizations of these outputs can be found in Appendix B. The important difference between pilot models was shown in the selection of medium priority areas, or where the transition of high to low priority lies. Managers may require locations of both high and medium priority stands to target for ecological restoration. With a dispersal kernel of 80m, the model had difficulty discerning between areas of higher and lower priority due to the low overall availability of coniferous forest within 80 m on the landscape. Generally, all stands within 80 m were high priority and the medium and low priority stands were not contiguous and consisted of individual cells scattered throughout the landscape. The 500 m dispersal kernel model showed larger priority patches, but the area surrounding these high priority areas was of significantly lower value, indicating the model is including stands within 500 m as priority and those outside as not priority. The 1000 m model had similar priority areas to the 500 m model, but with a more gradual transition between high and low priority, thus allowing for easier identification of medium priority areas. At the 2000m dispersal kernel, the majority of coniferous stands are naturally located within 2000 m of other coniferous stands, and connectivity is thus relatively equal across the landscape and no longer driving the prioritization analysis and thus priority begins to lose its significance.

In addition, the park is interested in planting trees beyond areas that a remnant spruce stand could naturally expand to. In the absence of compelling biological evidence to choose any one specific dispersal kernel, I selected the 1000 m (1 km) dispersal kernel as it would incorporate a larger range of connectivity that active reforestation could support. In addition, it ensured the prioritization was still driven by connectivity between stands, but also identified contiguous areas of medium priority. Although 1000 m is larger than the seed dispersal estimates for balsam fir and black spruce, it does incorporate larger ranges as required by American marten, Bicknell's thrush and Canada lynx (Table 3.4). Therefore, while this is still a structural connectivity analysis (considers the physical extent of features and habitat on the landscape), targeting larger landscapes to connect is more likely to support functional habitat connectivity for these forest-dependent wildlife species at risk.

3.2.4.1 Structural connectivity of coniferous forest at individual time steps

Five models of structural connectivity were produced for coniferous forest cover at each time step (1972, 1989, 1999, 2009, 2019). Each of these individual time step models is named Coniferous [Year], so for example the model of coniferous forest structural connectivity using 1972 data is titled “Coniferous 1972”. Coniferous forest cover data was input as an individual feature in each model, with a weight of 1 and a dispersal kernel of 1 km (Table 3.5). Zonation recommends simple weight schemes to ensure outputs can be better understood and interpreted, therefore the default weight of 1.0 for all forest cover layers was chosen. All other Zonation parameters were left at their default settings.

Table 3.5. Description of input data used in Zonation prioritization models.

Input data	Model use	Resolution	Source
1972 Coniferous	Coniferous 1972	30 m	Parks Canada
1989 Coniferous	Coniferous 1989	30 m	Parks Canada
1999 Coniferous	Coniferous 1999	30 m	Parks Canada
2009 Coniferous	Coniferous 2009	30 m	Parks Canada
2019 Coniferous	Coniferous 2019; Forest connectivity in 2019; Tree planting prioritization	30 m	Parks Canada
2019 Deciduous	Forest connectivity in 2019; Tree planting prioritization	30 m	Parks Canada
2019 Mixed	Forest connectivity in 2019; Tree planting prioritization	30 m	Parks Canada
2019 Disturbed	Forest connectivity in 2019; Tree planting prioritization	30 m	Parks Canada
2021 Non-forest	Forest connectivity in 2019; Tree planting prioritization	30 m	Nova Scotia Forest Inventory
1972 Coniferous less 2019 coniferous	Tree planting prioritization	30 m	Scanlan, R.
1989 Coniferous less 2019 coniferous	Tree planting prioritization	30 m	Scanlan, R.
1999 Coniferous less 2019 coniferous	Tree planting prioritization	30 m	Scanlan, R.
2009 Coniferous less 2019 coniferous	Tree planting prioritization	30 m	Scanlan, R.

The outputs of these models were then analysed in ArcGIS Pro. I determined the proportion and created visualizations of the highest value cells (top 10%) in each model that lies within protected areas. Using the raster calculator, I subtracted adjacent time step outputs (i.e., 1972 minus 1989, 1989 minus 1999, etc.) to determine areas of increase and decrease in prioritization throughout the study area.

Next, a model titled “Forest connectivity 2019” was built using all four forest class data available for 2019 (‘deciduous’, ‘mixed,’ ‘coniferous’, and ‘disturbed’), as well as the non-forest layer created from the Nova Scotia Forest Inventory (NS DNRR, 2021), as shown in Table 3.5. The four forest classes were assigned a dispersal kernel of 1 km, while the non-forest layer was given a dispersal kernel of 0 km, as connectivity to non-forested areas is not a priority.

3.2.4.2 Modelling priority areas for treeplanting

Tree planting prioritization is based on both current and historical forest connectivity conditions. Four raster layers were created to represent all areas which contained coniferous forest in a previous time step, but not in 2019, to be used as inputs for the “Tree planting prioritization” model. A simple raster calculation using ‘2019 coniferous forest’ – ‘[Year] coniferous forest’ across each time step was conducted to achieve this. These four layers represent cells of forest loss between historical time steps and 2019 (Figure 3.13). These forest loss layers were included as separate features with a dispersal kernel of 1km and a weight of 1, so that their weights accumulate. Coniferous forest that was present at multiple previous time steps, but not in 2019, was then given higher priority than cells that only contained coniferous forest at one specific time step Therefore in the output, areas that both once contained coniferous forest but no longer do *and* which are connected to other stands of coniferous forest will be prioritized in the model. These areas that once supported coniferous species are seen as recommended priority sites for tree planting, given they previously contained coniferous forest and are considered spatially close enough to be connected.

Finally, tree planting efforts will be limited to areas which do not currently contain forest cover. Three individual maps were produced using the “Tree planting prioritization” model output. The initial map, titled "Restoration opportunity" is the original, unaltered output. Next, the output was edited to only show areas which did *not* contain coniferous, deciduous, or mixed forest cover in 2019, and is titled "Tree planting priority areas". The final map contains the top 10% value cells from the "Tree planting prioritization" model, that also did not contain 2019 forest cover and is titled "Top 10% tree planting priority areas". These high value areas were correlated with the Nova Scotia Forest Inventory to identify the proportion of landcover types and dominant tree species represented.

Table 3.6 below summarizes the weights of landscape features included in all three model categories. The first column represents the "[Year] coniferous" models of structural connectivity at individual time steps. The second column contains the "Forest connectivity in 2019" model that includes all forest cover data for 2019. The third column shows all data included in the "Tree planting prioritization" model.

Table 3.6. Weighting of all layers included in models. Features with higher value, positive weights will be given priority in the model and retained towards the end of the algorithm. Areas that contain concentrations of high weighted features will be prioritized. Conversely, negative features are considered undesirable and removed earlier in the prioritization process.

	[Year] connectivity	Forest connectivity in 2019	Tree planting prioritization
1972 coniferous	1	-	-
1989 coniferous	1	-	-
1999 coniferous	1	-	-
2009 coniferous	1	-	-
2019 coniferous	1	1	1
2019 deciduous	-	1	1
2019 mixed	-	1	1
2019 disturbed	-	2	2
2022 non-forest	-	-1	-1
Coniferous loss 1972 to 2019	-	-	1
Coniferous loss 1989 to 2019	-	-	1
Coniferous loss 1999 to 2019	-	-	1
Coniferous loss 2009 to 2019	-	-	1

3.3 RESULTS

3.3.1 Quantifying coniferous forest loss over time

By layering the data chronologically, a visual examination of coniferous cover across all timesteps indicates many stands present in 1972 were lost and never recovered (Figure 3.3).

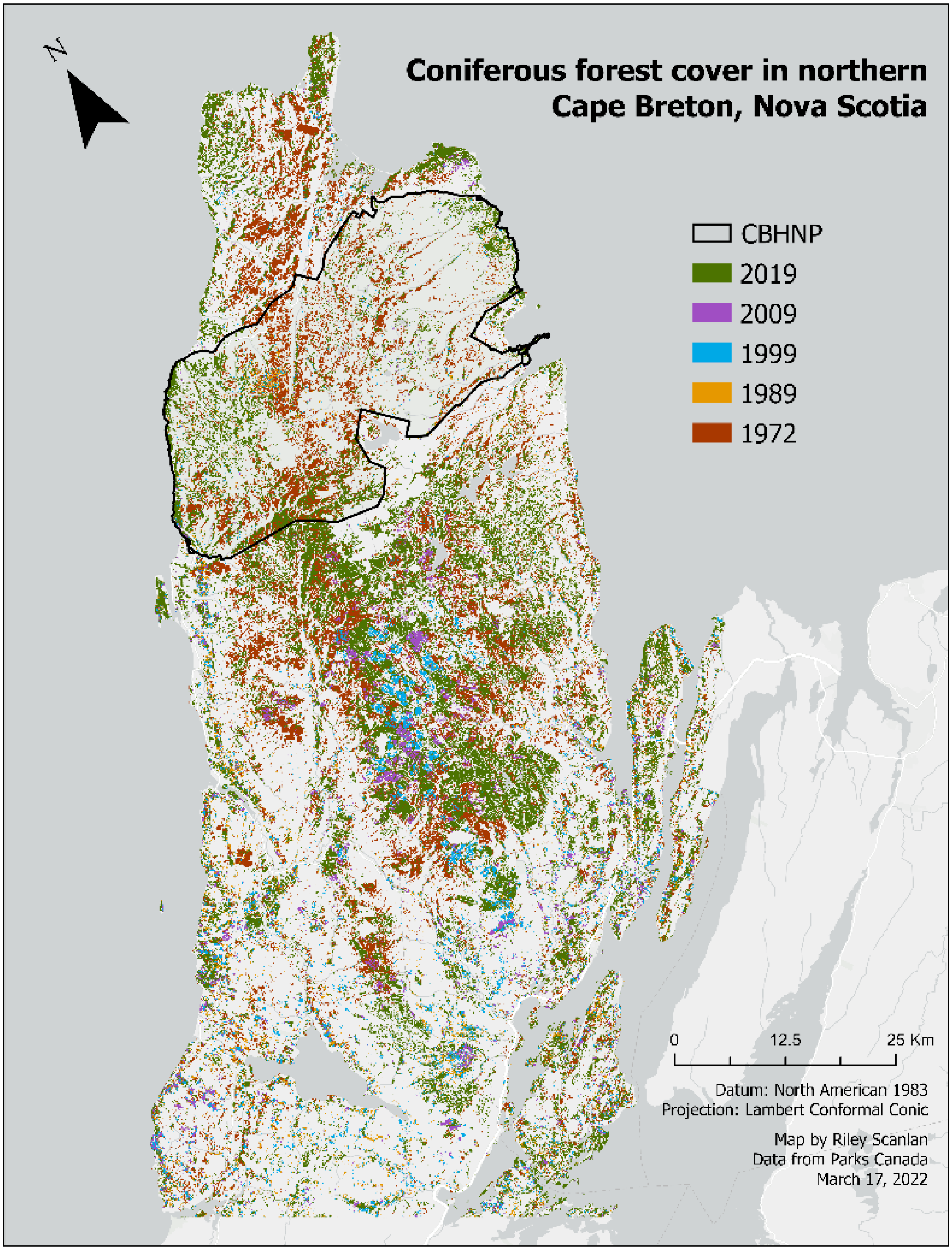

Figure 3.3 Polygons represent coniferous forest cover at corresponding time step. Layers are shown chronologically, with most recent layers on top. I.e., areas shown in red contained coniferous forest in 1972 and not at any other time.

Large tracts of coniferous forest were lost between 1972 and 1989, with nearly 44% of coniferous forest in northwestern Unama'ki being converted to other land cover types (Figure 3.4). Though coniferous forest began to increase in area in subsequent decades, there remains a 32% loss in coniferous forest between 1972 and 2019 (Figure 3.4). Loss of coniferous forest was not, however, uniform across northwestern Unama'ki. More coniferous forest was lost within protected areas than outside protected areas at each time step (Figure 3.4, Figure 3.5).

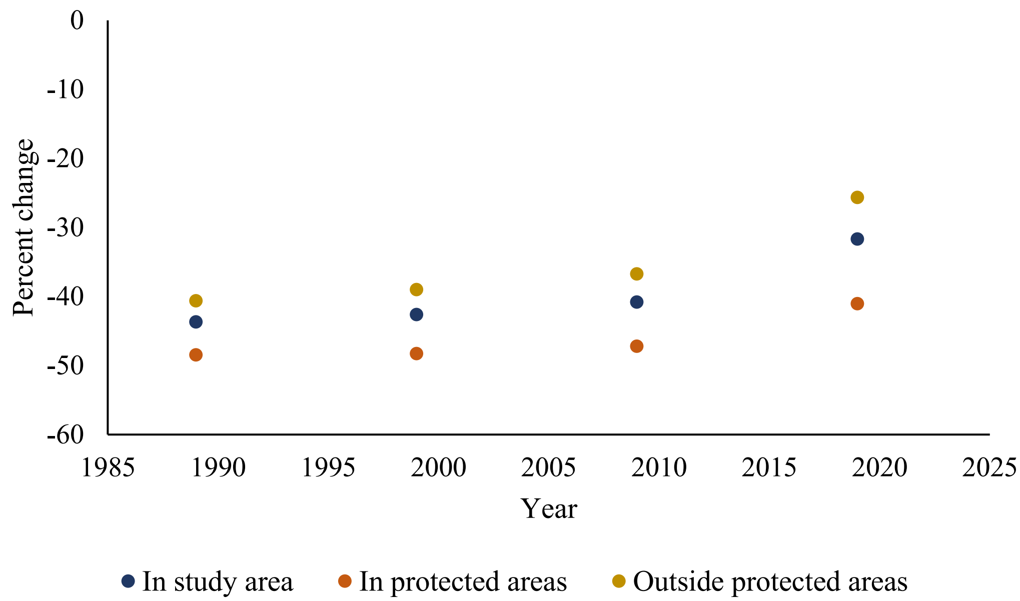

Figure 3.4 Coniferous forest lost between 1972 and all subsequent time steps.

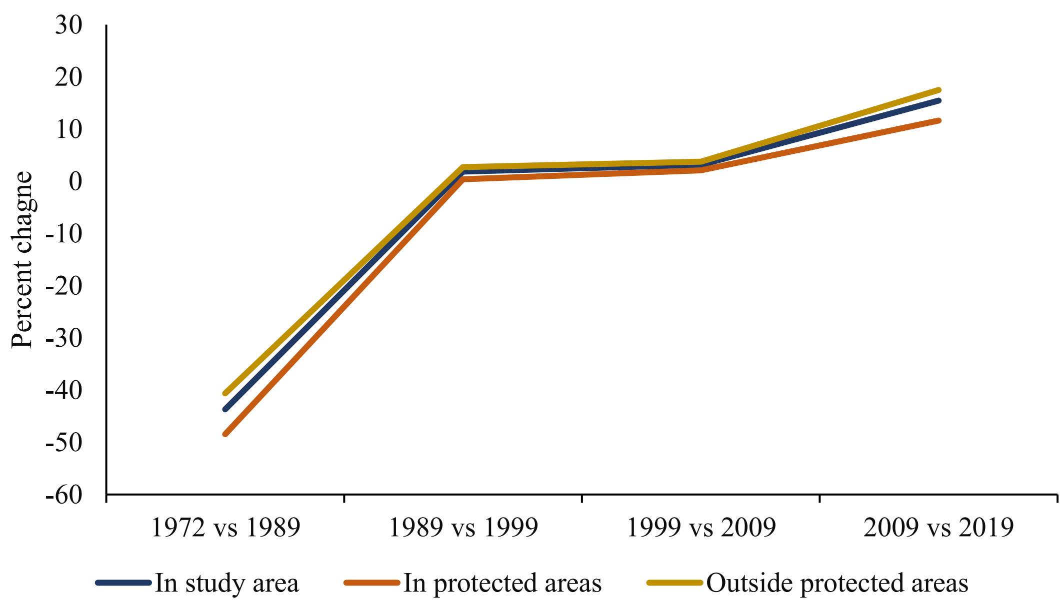

Figure 3.5 Coniferous forest lost between adjacent time steps.

The analysis of mean forest stand area, perimeter and NPI at each time step help contextualize the overall trend of forest loss following the spruce budworm outbreak (Table 3.7).

Table 3.7. Average area, perimeter, and normalized perimeter index (NPI) of coniferous forest stand polygons for each time step as well as all years combined (total).

Year	N	Mean area (m^2) ± std dev	Mean perimeter (m) ± std dev	Mean NPI ± std dev
1972	72,252	18,310 ± 324,770	579 ± 5,406	0.781 ± 0.15
1989	70,556	10,558 ± 80,976	435 ± 1,740	0.786 ± 0.14
1999	65,361	11,612 ± 82,633	453 ± 1,690	0.783 ± 0.14
2009	64,467	12,145 ± 91,205	464 ± 1,858	0.783 ± 0.14
2019	73,447	12,307 ± 192,312	465 ± 3,630	0.785 ± 0.14
Total	346,083	13,042 ± 184,533	480 ± 3,271	0.784 ± 0.15

The standard deviation for each variable is quite large due to the data being heavily skewed, with the majority of stands having a smaller area and perimeter. Results of the one-way analysis of variance (ANOVA) determined significant differences in mean coniferous forest stand area (df = 4, F = 18.77, $p \leq 0.01$) and perimeter (df = 4, F = 21.02, $p \leq 0.01$) between the 1972 data and all subsequent time steps (Figure 3.6). In particular, the 1972 layer showed a larger area of coniferous forest (mean = 18,309.8 ± 324,770 m^2, N = 72,252). As with area, mean perimeter for the 1972 data was significantly larger per stand (mean = 579.5 ± 5,406 m, N = 72252) when compared to all other years.

Interestingly, the NPI analysis found significant differences ($p < 0.05$) at different time steps than the area and perimeter analyses (Table 3.8, Figure 3.7). See Appendix C for full post hoc analysis. The mean normalized perimeter index increased significantly between 1972 and 1989, 1989 and 1999, and between 2009 and 2019 ($p<0.05$). The only adjacent time steps that were not significantly different were 1999 and 2009. Each time step after 1972 has a larger mean NPI than the 1972 data.

Table 3.8. Post hoc analysis of one-way ANOVA of normalized perimeter index using Tukey HSD.

	1972	1989	1999	2009	2019
1972	-	<0.001*	0.002*	0.094	<0.001*
1989	<0.001*	-	0.001*	<0.001*	0.528
1999	0.002*	0.001*	-	0.752	0.144
2009	0.094	<0.001*	0.752	-	0.004*
2019	<0.001*	0.528	0.144	0.004*	-

* The mean difference is significant at the 0.05 level.

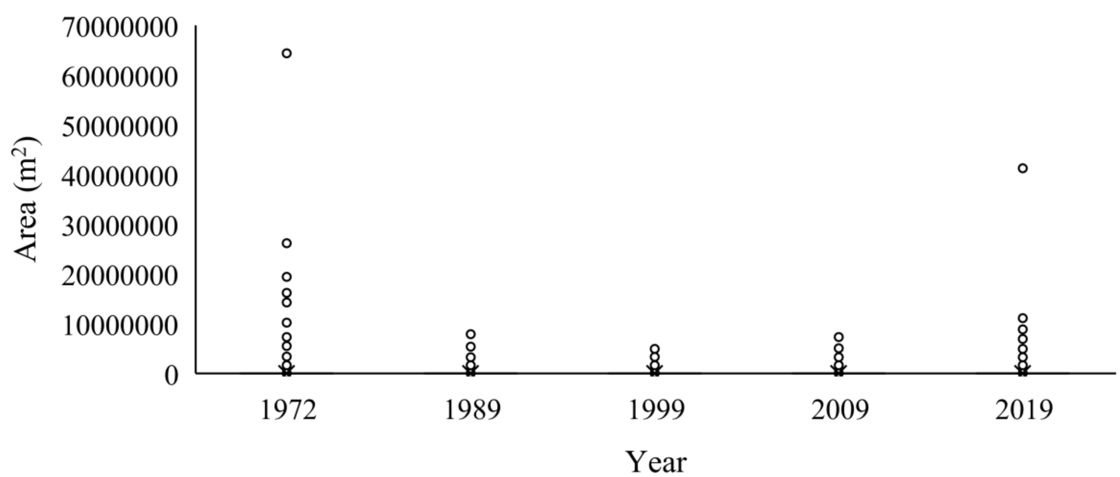

Figure 3.6 Boxplot showing distribution of coniferous stand area (m^2) for each time step. Data is highly skewed,with most stands being small and relatively few large stands.

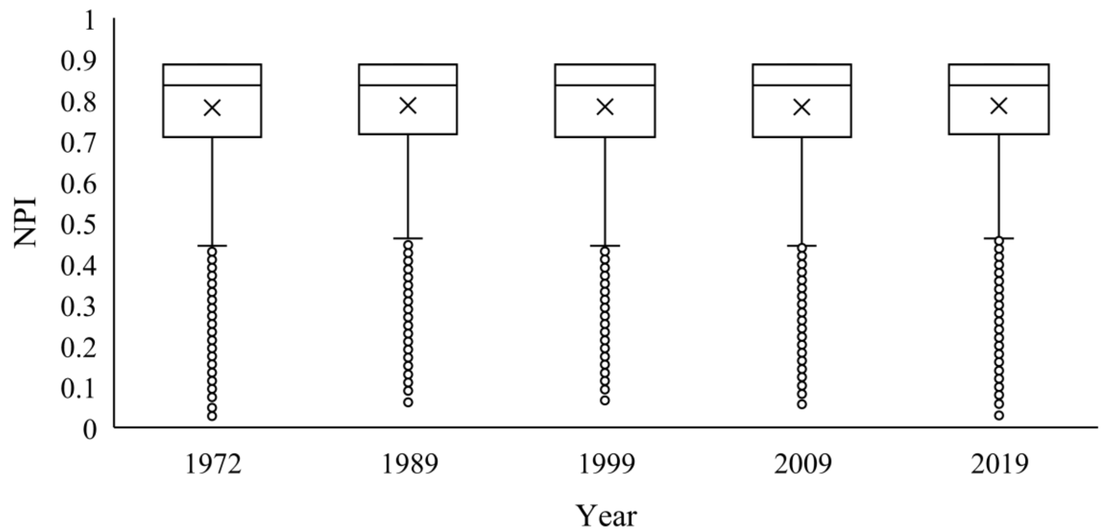

Figure 3.7 Boxplot showing distribution of normalized perimeter index (NPI) values for coniferous stands at each time step.

While an understanding of the degree to which coniferous forest cover changed over time is useful, an understanding of where this forest change occurred provides decision makers more information. Figure 3.8 shows overall coniferous forest change between all years that were found to be significantly different in area and perimeter (see Appendix D for larger images of individual maps).

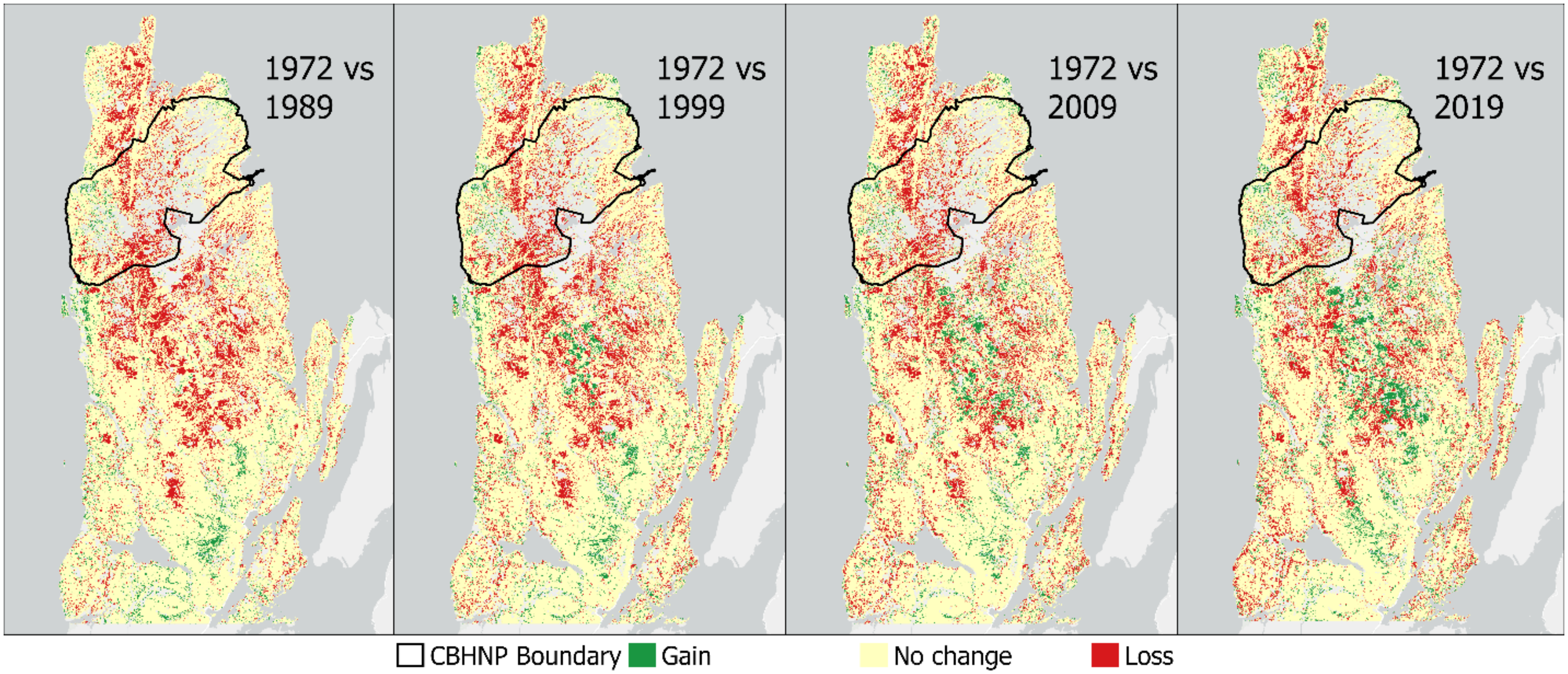

Figure 3.8. Coniferous forest change between various time steps. Areas in green indicate stands that converted to coniferous forest between the two time steps, while red indicates areas where coniferous forest was lost and converted to another landcover type.

Some stands of coniferous forest have increased in areas south of the park in recent time steps compared to 1972 (Figure 3.8). Mean and total coniferous forest stand area and perimeter per square kilometer was also calculated. Visual representation of outputs can be found in Appendix E.

3.3.2 Structural connectivity

I analysed: 1) structural connectivity of coniferous at each time step and 2) structural connectivity of all forest types in 2019. The first group of models used coniferous forest data at each individual time step to provide insight to the connectivity of the landscape at that time (Figure 3.9). See Appendix F for larger individual maps.

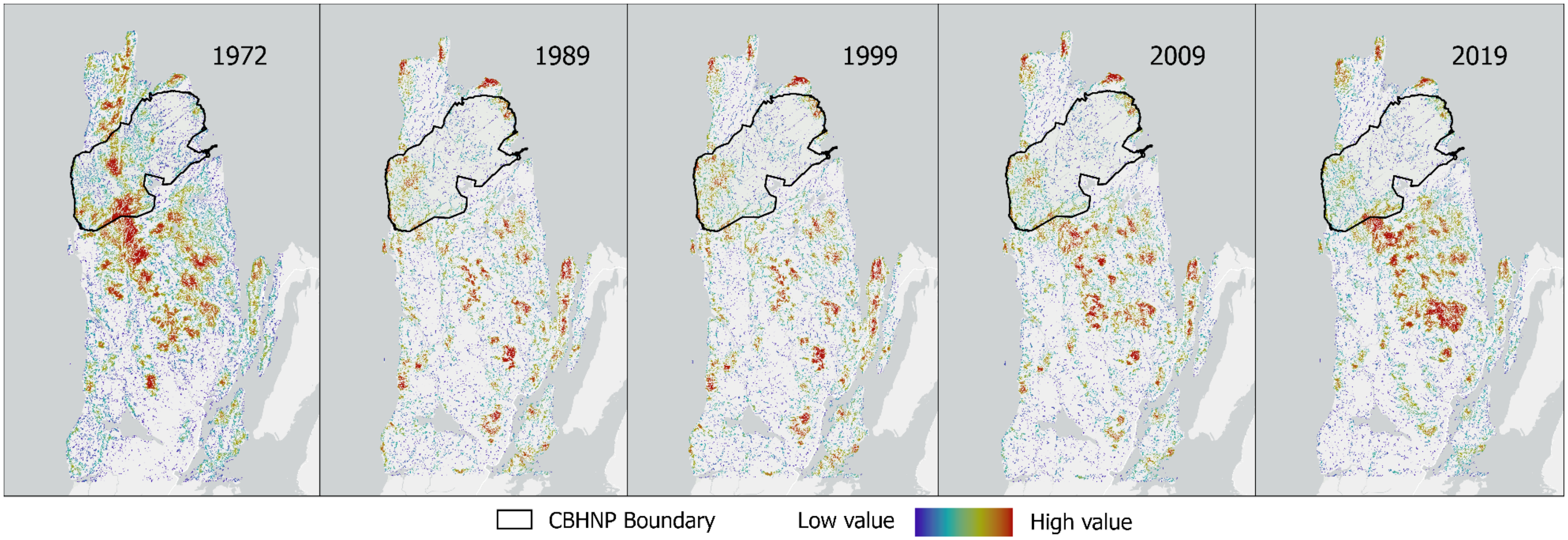

Figure 3.9. Structural connectivity of coniferous forest at individual time steps using dispersal kernel of 1 km. Cape Breton Highlands National Park (CBHNP) shown in black border.

Prior to the spruce budworm outbreak, large tracts of coniferous forest in the centre of the study area contributed substantially to landscape connectivity. However, the loss of those contiguous patches in the center of the study area shifted priority stands elsewhere. The areas of high priority, according to their density of features and connectedness, become more isolated in 1989 and 1999 (Figure 3.9). By 2019, stands lost within the park and center of the study area began to return and are again considered higher value (Figure 3.9). Further analysis of the individual model outputs shows that in 1972, approximately half of all high value areas (top 10%) were found in protected areas (Table 3.9; Figure 3.10). This proportion drops between 1972 and 1989 and continues to steadily decline until the proportion remaining in 2019 is about 21% (Table 3.9). In addition, about one quarter of high value cells in 1972 were located in CBHNP. This proportion decreased drastically to 8% by 1989 and remains at 2.5% as of 2019. This distribution can also be seen in Figure 3.10. To put this in context, protected areas cover about 33% of landmass in the study area, and CBHNP covers 16.9%.

Table 3.9. Proportion of high value cells (defined as top 10% in model output), from individual time step models of structural connectivity, found within protected areas and CBHNP. Protected areas include all provincial, federal, and lands conserved as of December 2021.

	Proportion (%) of top 10% value cells	
Year	**In protected areas**	**In CBHNP**
1972	49.7	26.1
1989	34.6	8.01
1999	31.9	4.83
2009	30.1	1.30
2019	21.3	2.55

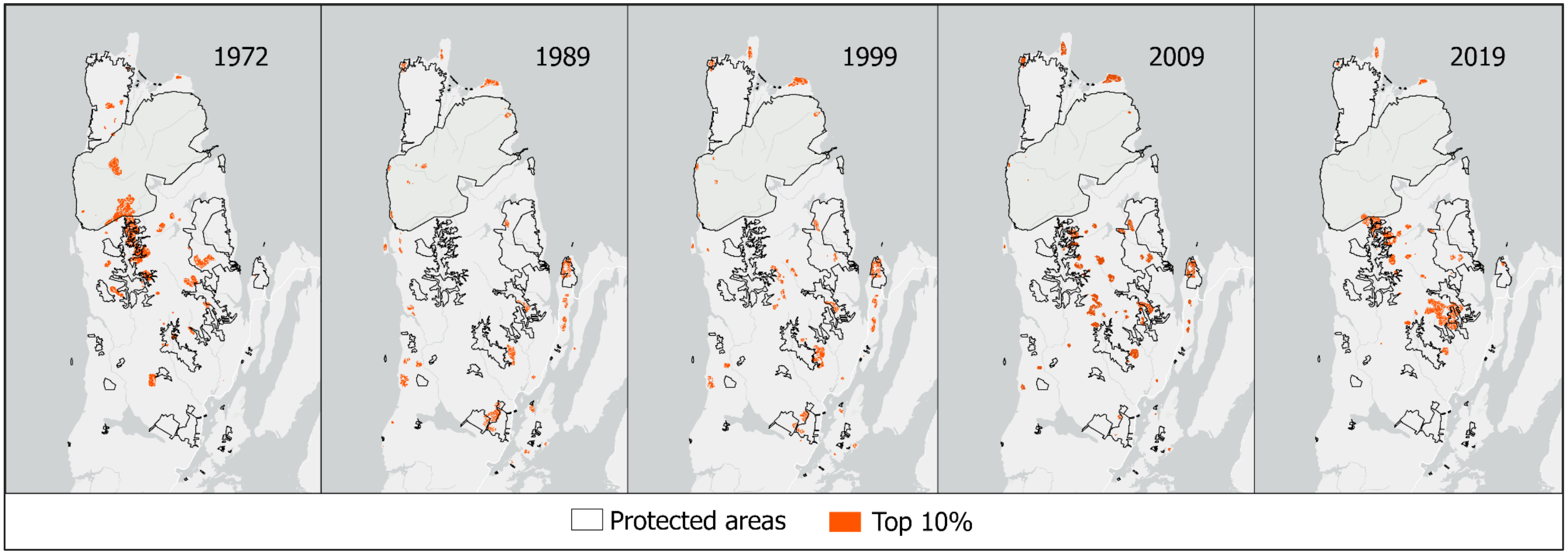

Figure 3.10. Distribution of top 10% highest value cells calculated in “[Year] coniferous” connectivity models (orange polygons) as compared to protected areas (black outlined polygons).

Large areas of coniferous forest that persisted between 1972 and 1989 increased in value (Figure 3.11). Between the next two time steps (1989 to 1999 and 1999 to 2009), many of the stands decreased in value. Then again, between 2009 and 2019, large areas have increased in value.

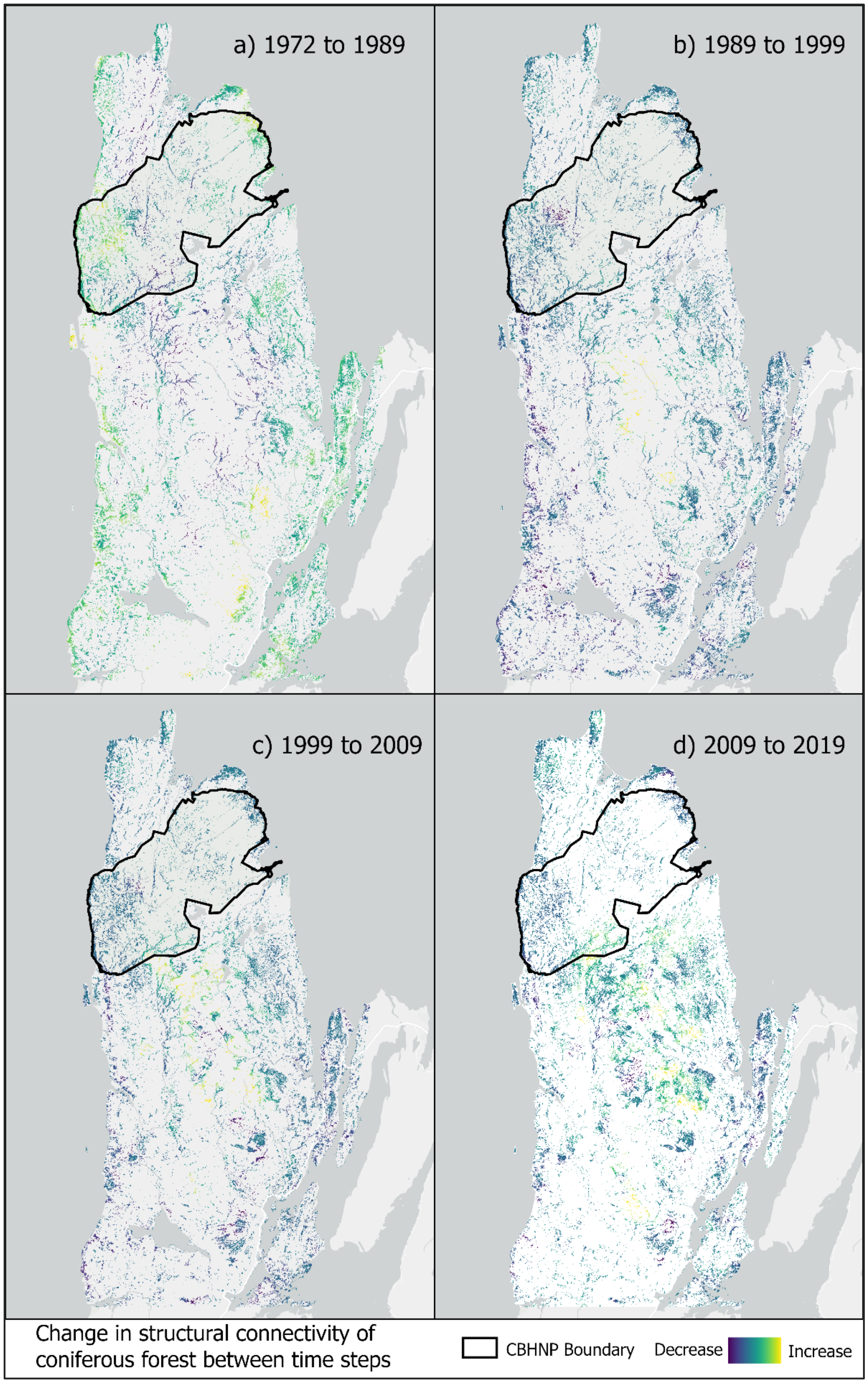

Figure 3.11. Adjacent “[Year] coniferous” models subtracted to determine areas of decrease (dark blue) and increase (yellow) in value to connectivity.

The output of a Zonation analysis is a raster layer that ranks each cell between 0 and 1. It is important to note that while this output is a ranking of the relative importance of each cell, it is not an absolute value. Therefore, though the configuration of an individual forest stand may not change between two time steps, if other, previously larger and more connected stands in the landscape become lost or fragmented, the unchanged stand may now contribute relatively more to overall habitat and landscape connectivity.

Figure 3.12 below displays the "Forest connectivity in 2019" model including all forest classes (disturbed, mixed, coniferous, deciduous) and non-forest to represent current conditions.

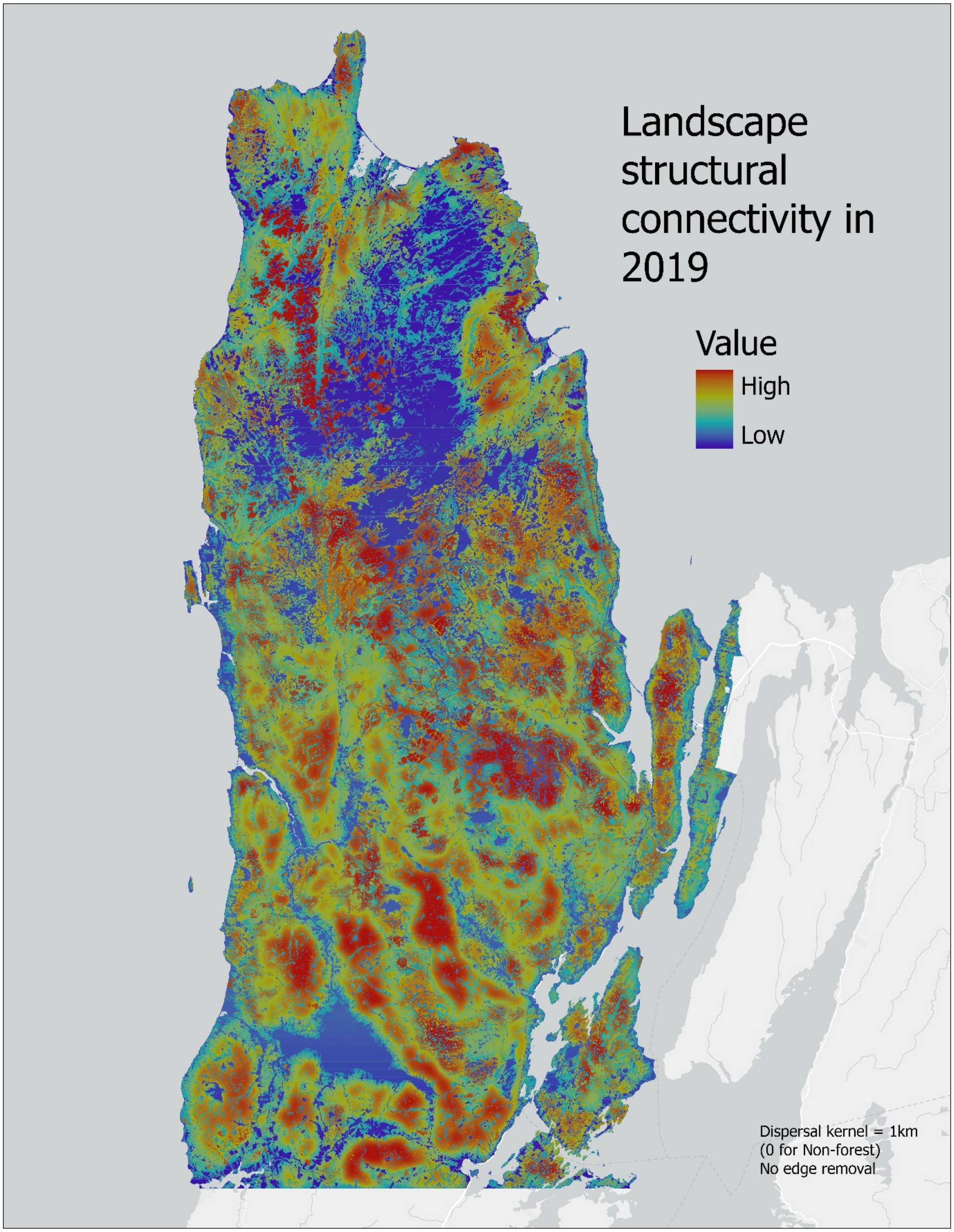

Figure 3.12. Structural connectivity analysis using the following forest types, weighting in brackets: coniferous (1), deciduous (1), mixed (1), disturbed (2) and non-forest areas (-1). Forest cover given dispersal kernel of 1 km, non-forest given dispersal kernel of 0 km.

3.3.3 Prioritization of areas for tree planting

The final model included in this research was built to guide forest restoration and was informed by outputs of the previous section. The “Tree planting prioritization” model includes all layers of historical forest loss, 2019 forest cover and non-forest as inputs. The forest loss layers are shown in Figure 3.13.

The output map, titled “Restoration opportunity” shows that areas of high priority for tree planting closely align with the ‘disturbed’ 2019 data layer, but also the historical coniferous forest cover layers (Figure 3.14). The removal of present-day forest cover in the “Tree planting priority areas” map highlights priority areas that do not contain forest cover as of 2019 (Figure 3.15). The data in Figure 3.15 was visualized using equal interval classification bins between 0 and 1, according to the value each cell was assigned in the original model.

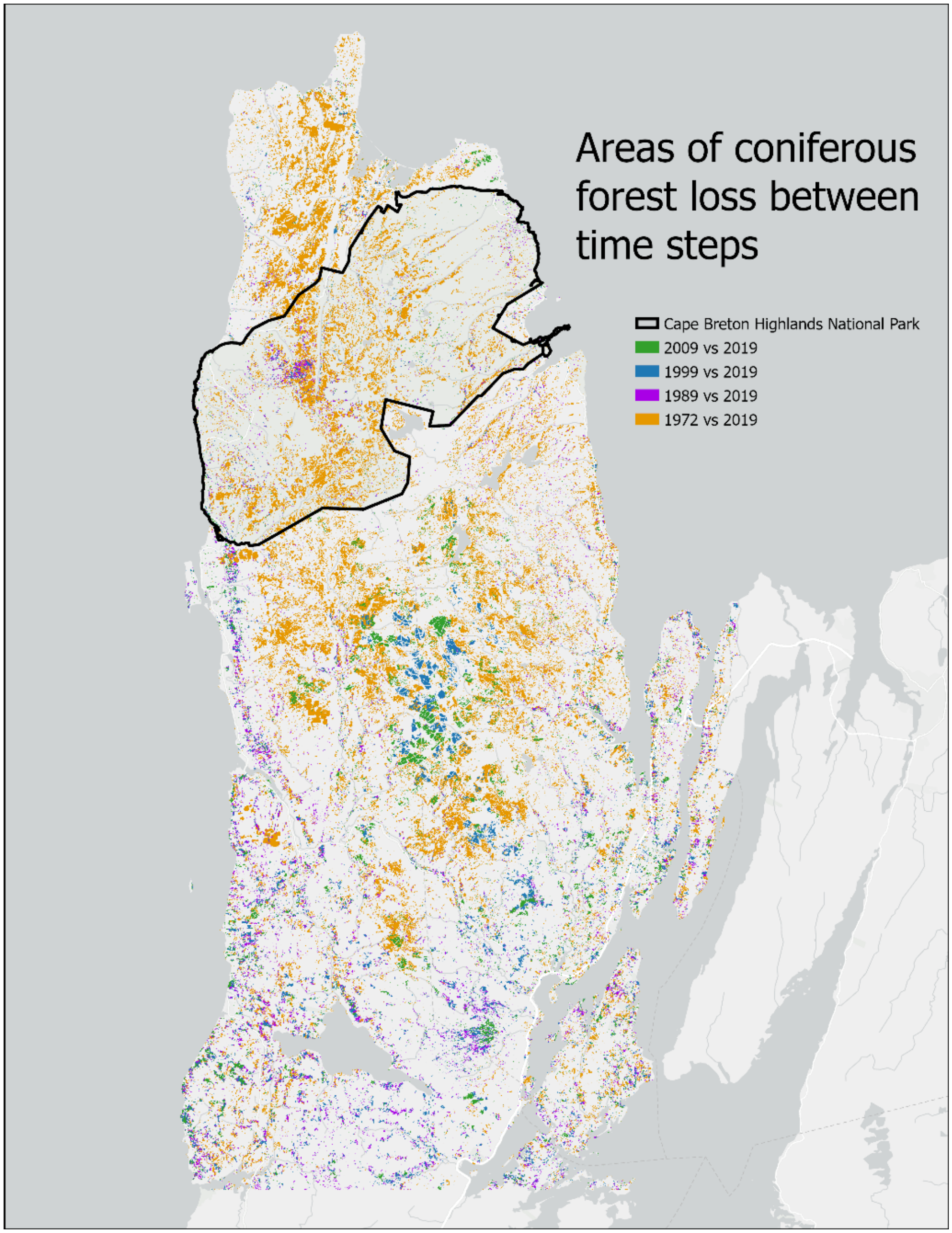

Figure 3.13 Layers of forest loss between historical time steps and present day: 2019 minus 2009; 2019 minus 1999; 2019 minus 1989; 2019 minus 1972. Layers are ordered chronologically, so stands that were present in several earlier timesteps are only seen in most recent layer.

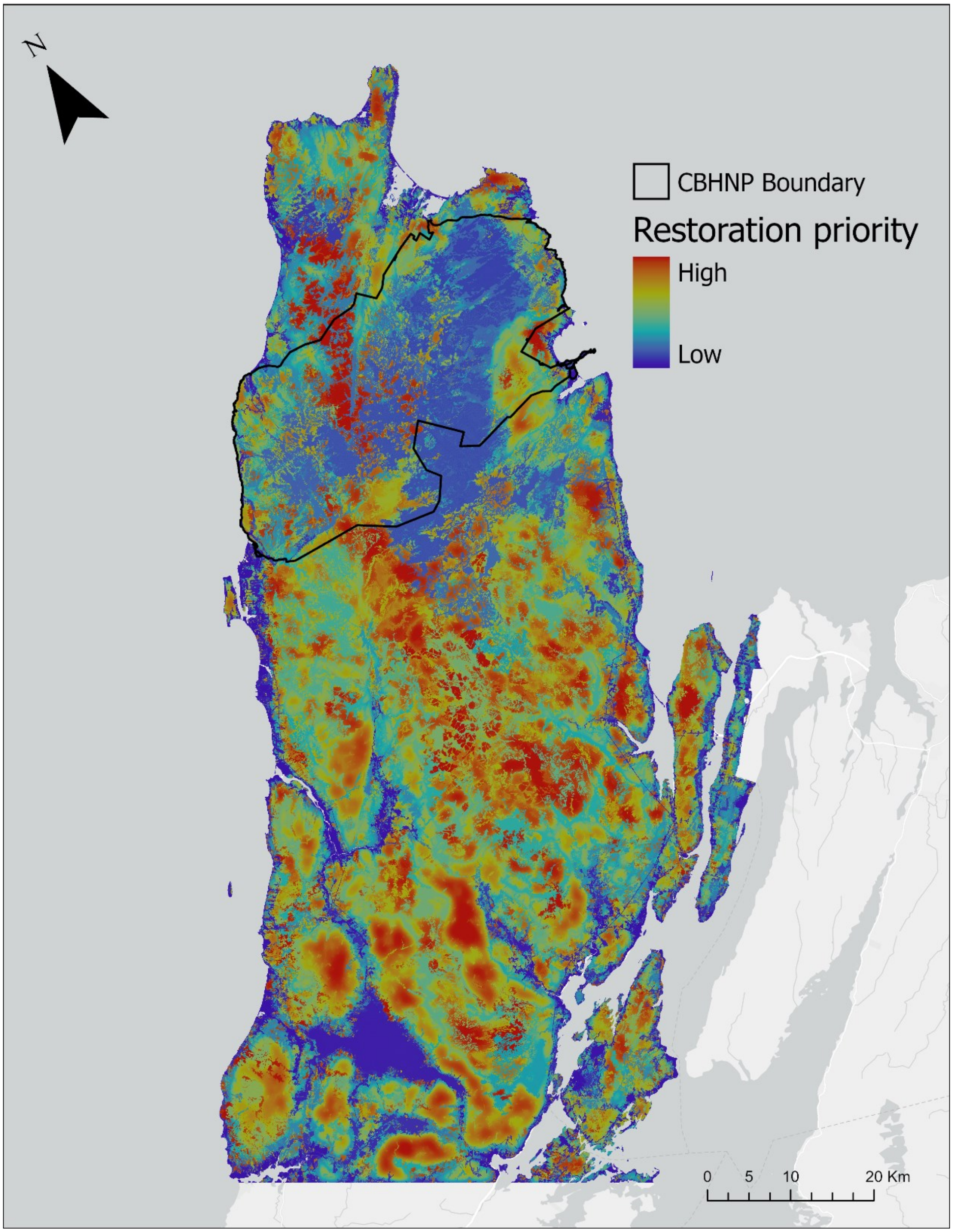

Figure 3.14 Restoration opportunity map shows priority areas for tree planting. Input data included all forest types of 2019, non-forest data and forest loss data between all time steps and 2019.

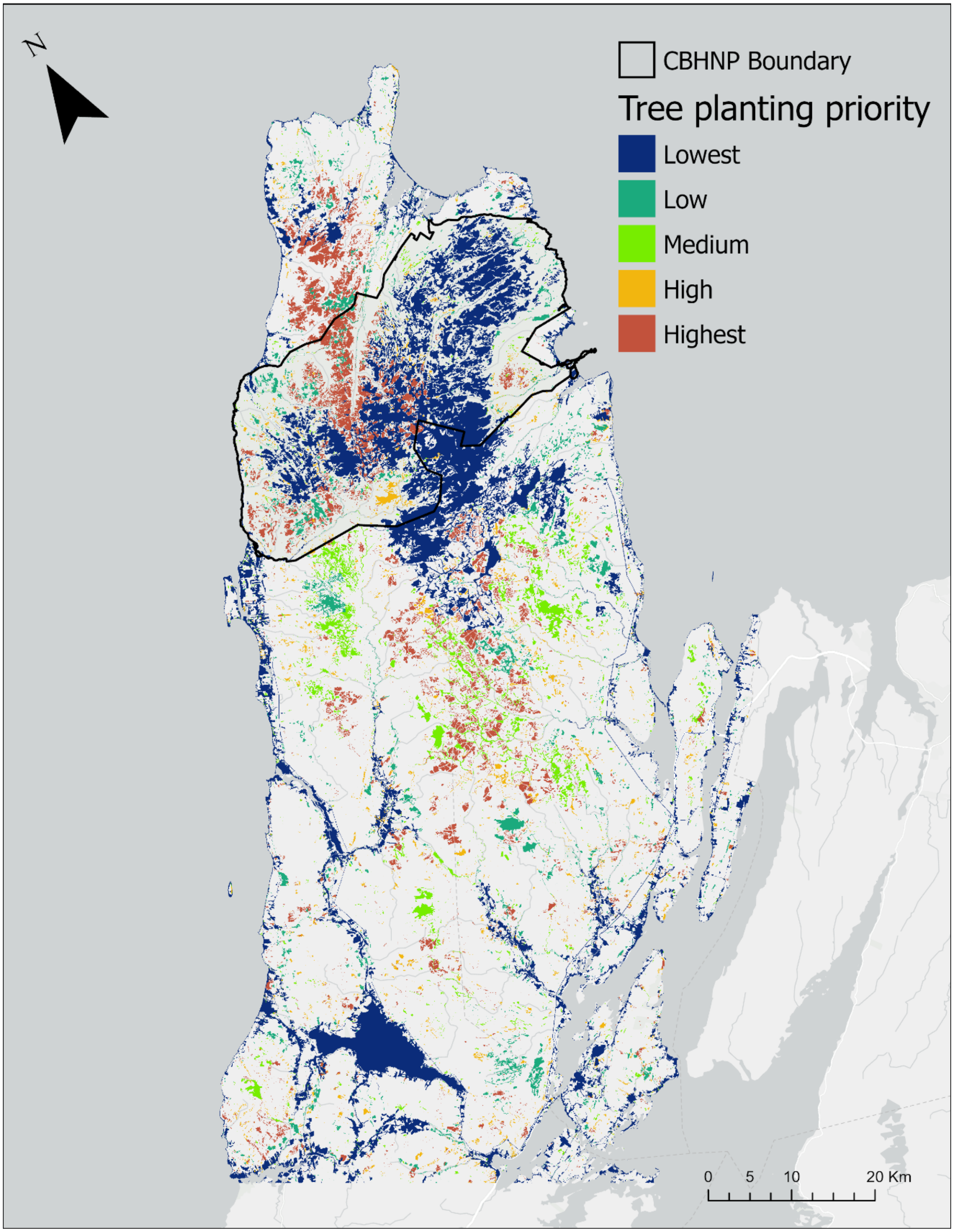

Figure 3.15 Tree planting priority areas map shows output of tree planting prioritization model with all of 2019 forest cover data removed. Data is classed into equal bins.

Despite the 2019 forest cover data being removed from the “Tree planting prioritization model” in the “Tree planting priority areas” map (Figure 3.15), nearly half (42%) of the top 10% value cells in Figure 3.15 are categorized as a natural stand by the NS Forest Inventory (NS DNRR, 2021; Table 3.10). Balsam fir (26%), white spruce (20%) and black spruce (10%) made up the dominant species in these priority areas (Table 3.11).

Table 3.10. Total area and proportion of landcover types identified in top 10% value cells in tree planting prioritization model. Landcover types were taken from NS Forest Inventory. See Appendix A for full description of landcover types.

Fornon Field	**Landcover**	**Area (hectares)**	**Percent total by area**
0	Natural stand	32368	41.9
16	Moose meadow	10259	13.3
20	Plantation	6282	8.1
1	Treated (unclassified	5154	6.7
12	Treated stand (classified)	4239	5.5
60	Clear cut	4128	5.4
	Other	4114	5.3
72	Open bogs	4033	5.2
73	Treed bogs	2935	3.8
70	Wetlands general	2014	2.6
9	Dead	843	1.1
85	Barren	790	1

Table 3.11. Forest species composition in areas prioritized as the top 10% most valuable for treeplanting to restore boreal forest connectivity. Tree species coverage was obtained from the NS Forest Inventory (NS DNRR, 2021).

Dominant species	**Area (ha)**	**Percent total**
Balsam fir (*Abies balsamea*)	20021	25.95
unidentified	17960	23.28
White spruce (*Picea glauca*)	15327	19.86
Black spruce (*Picea mariana*)	7514	9.74
Yellow birch (*Betula alleghaniensis*)	4977	6.45
Sugar maple (*Acer saccharum*)	4689	6.08
White birch (*Betula papyrifera*)	3032	3.93
Unclassified softwood	1191	1.54
Red maple (*Acer rubrum*)	1145	1.48
Unclassified hardwood	956	1.24
Eastern larch (*Larix laricina*)	231	0.30
Eastern hemlock (*Tsuga canadensis*)	42	0.05
Norway spruce (*Picea abies*)	25	0.03
Red spruce (*Picea rubens*)	16	0.02
Ash (Black [*Fraxinus nigra*]& White [*Fraxinus americana*])	14	0.02

The distribution of top 10% value stands can be seen in Figure 3.16 below.

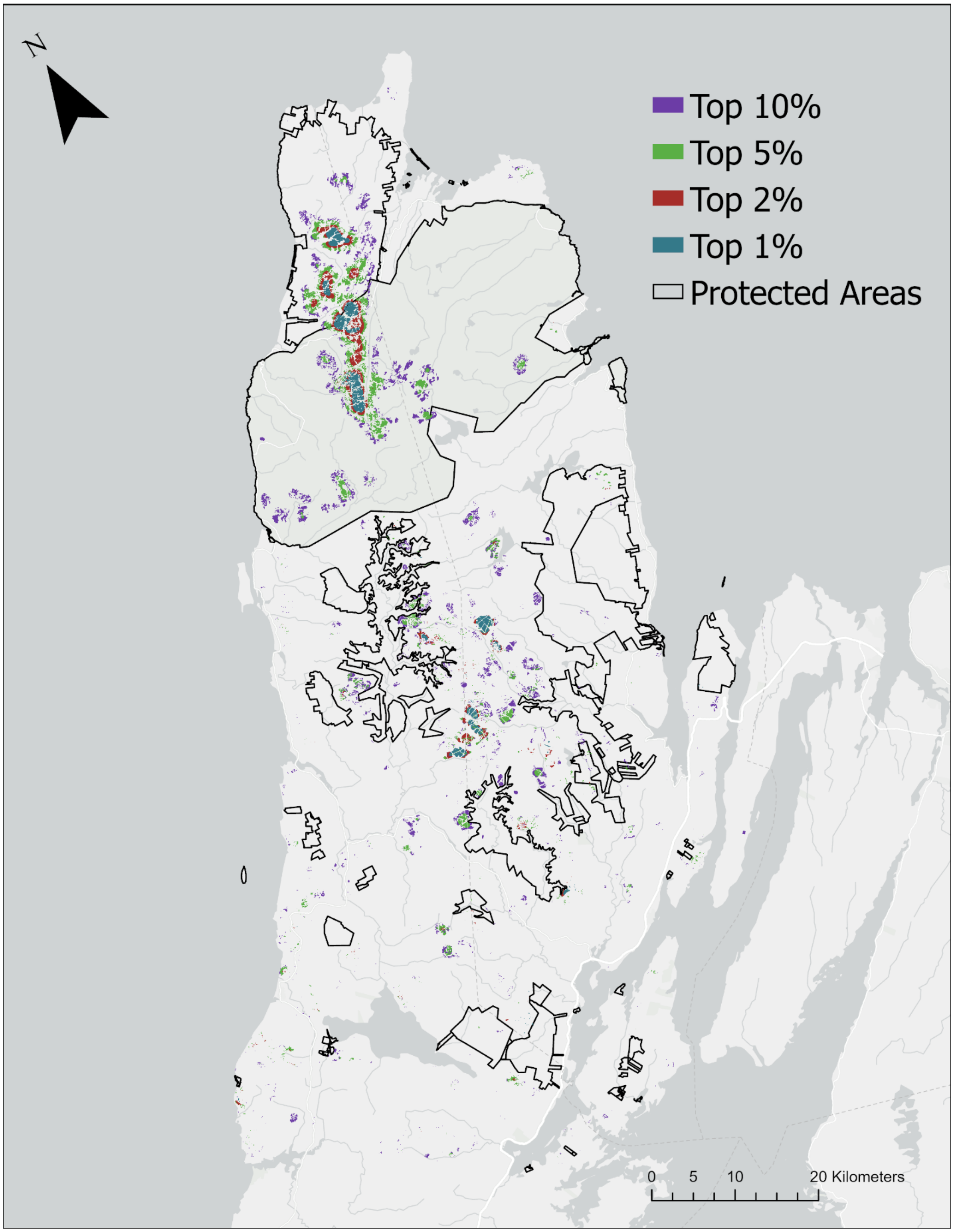

Figure 3.16. Top 10% tree planting priority areas defined as high priority in “Tree planting prioritization” model with cells that overlap 2019 forest cover removed. All protected areas shown in black bordered polygons.

A large portion of high priority sites for restoration are found in protected areas (60%), with over half of those being in CBHNP (Table 3.12).

Table 3.12. Distribution of high value (top 10%) areas in tree planting prioritization model between protected areas and Cape Breton Highlands National Park (CBHNP).

	Area (ha)	**Percent total (%)**
In CBHNP	5402	36.1
In all protected areas	9015	60.2
Total	14975	

3.4 DISCUSSION

3.4.1 Loss of coniferous forest cover

As other research has found, the significant amount of forest loss that occurred between 1972 and 1989 (Figure 3.4) can largely be attributed to the spruce budworm outbreak throughout the 1970s and subsequent over browsing by moose (Ostaff & MacLean, 1989; C. Smith et al., 2010). A density of 1 moose per square kilometer is the threshold where the Park considers the population transitions from Good to Fair conditions, according to their Ecological Integrity Monitoring Program (R. Smith et al., 2015). Moose abundance reached a high of 4.2 moose/km^2 in 2004, and dropped below 2moose/km^2 in 2006 (R. Smith et al., 2015). The population has remained consistently above the 1 moose/km^2 threshold as of 2015 (R. Smith et al., 2015). Moose may be avoiding hunters and human disturbance caused by development and forestry in forest outside the Park. In addition, CBHNP may provide higher quality habitat than elsewhere. Therefore, their population may be denser in the Park and the impact of moose browse in that area is extensive.

In addition, large tracts of forest damaged by spruce budworm were logged to salvage profits (Nova Scotia Department of Natural Resources, 1994). Areas previously logged were replanted with coniferous species and thereby contributed to the total amount of coniferous forest in later time steps. Cotton-Gagnon et al. (2018) found that logging following a spruce budworm outbreak can cause greater defoliation from SBW of remaining black spruce (which is naturally more tolerant to SBW than balsam fir) in subsequent outbreaks. The authors speculate that if greater defoliation of black spruce reduces that species' survival, the stand may shift to balsam fir dominance (Cotton-Gagnon et al., 2018). A balsam fir-dominated forest is then more susceptible to future SBW outbreaks. This present research did not distinguish forest stands by species and therefore cannot investigate these findings. However, further analysis may benefit from considering the susceptibility of harvested SBW-impacted stands.

In addition, the increase in coniferous forest in later time steps due to re-planting post-harvest could be used as a proxy for when we should expect to see forest cover return naturally in non-harvested areas, such as within the Park. Studies have shown that in some instances, forest recovery can occur at a faster rate following passive (not human influenced) restoration than active restoration, such as tree planting (Crouzeilles et al., 2017; Meli et al., 2017). However, disturbance type greatly influences the rate and success of forest succession (Crouzeilles et al., 2016). In this case, the insect outbreak disturbance was drastic. We can therefore conservatively expect that natural forest recovery following the spruce budworm outbreak should occur at a rate similar or slightly slower rate than the growth of trees planted post-harvest. Figure 3.9 shows that while coniferous forest now occurs in areas logged south of the park, it has not returned to the same extent in the Park. This is likely due to the lasting impact of overbrowse by moose which converted regenerating forested areas to grasslands (C. Smith et al., 2010). In addition, the logged areas contain a network of roads, which disrupts habitat and likely made the area less desirable for moose.

Overall, an incredible amount of coniferous forest present in 1972 was lost and never recovered both inside and outside Cape Breton Highlands National Park. Mean forest stand area and perimeter were both significantly larger in 1972 than in subsequent time steps, indicating a general decrease in stand size (Table 3.7). Further, while total forest cover decreased, the configuration of forest stands became less convoluted, shown in the increase in NPI (Table 3.7). This indicates that while total forest loss is causing landscape fragmentation, the configuration of remaining stands at the patch scale has not become more fragmented. Franklin et al. (2015) also found the impact of forest edges created by this spruce budworm outbreak was generally less severe than those produced from wildfires or clearcutting.

3.4.2 Coniferous forest structural connectivity

The impact of this forest loss on structural connectivity was yet to be examined prior to this research. Interestingly, protected areas prior to the SBW contained nearly half of the high priority areas (Table 3.9) despite only taking up 33% of the land mass in the study area. Particularly, CBHNP represented a disproportionate amount of high value areas, with 26% of priority areas located in the park, which itself only makes up 17% of the study area. This exemplifies the ecological importance and contributions of the National Park to the landscape.

The decrease in high value areas within CBHNP between 1972 and 1989 was drastic (26% to 8%). This is likely because areas of high balsam fir, white spruce and black spruce density and continuity are ideal for the spruce budworm.

The considerable loss of coniferous forest cover between 1972 and 1989 led to the increased prioritization of persistent stands (Figure 3.4, Figure 3.11). Stands which persisted between 1972 and 1989 that were previously medium to low value, then became high value in 1989 (Figure 3.11). This implies that the connectivity quality of forest stands remaining is lower than the original stands that were lost. In addition, the characteristics of high value areas in 1972 changed following disturbance throughout the study area. The top 10% value cells in 1972 were found in fewer, larger core patches of coniferous forest generally inland. In 1989, these top 10% cells tended to be in smaller patches of coniferous forest located towards the coast. In following time steps, larger, high priority patches began to form in inner portions of the study area, closer to their distribution in 1972. However, this return occurred largely outside protected areas and can be predominantly attributed to post-harvest tree planting. Furthermore, the structural connectivity of planted stands outside protected areas is likely overestimated, as logging roads bisecting these stands would not be captured at the 30 m^2 resolution of the forest cover data.

It is important to again note the interpretation of Zonation outputs is important here. The value of a cell is assigned according to the weight of features present and the connectivity to other features of interest. Cells are assigned values iteratively, creating a ranking of cells between 0 and 1 as the output. Therefore, the value of a cell at any one time step is not its absolute value for connectivity but is relative to the configuration and value of all other cells on the landscape. When, in the time between 1972 and 1989, large areas of high value, contiguous forest were lost, cells that were not highly ranked in 1972 became highly ranked in 1989 not by their absolute value for connectedness, but by virtue of being remnant coniferous stands on the landscape. Therefore, coniferous stands that were defoliated and either over-browsed or were logged, were also those that were high value, connected stands in 1972. It is hypothesized that connected, coniferous dominant stands may be preferentially selected and most impacted by spruce budworm, as these areas provide a consistent source of habitat and food.

3.4.3 Prioritizing areas for tree planting

Ecologically, CBHNP is well situated to conduct tree planting efforts. In my analysis, 66% of the high value areas for tree planting were located in protected areas, and 36% of all high value areas were in CBHNP. Given protected areas make up 33% of the study area and CBHNP only 17%, these proportions are high. This is likely due to the concentration of high value cells for forest structural connectivity in the Park (26%) and in protected areas (50%) in 1972 (Table 3.9). We can therefore be confident that the high priority areas are capturing stands which, if they were the focus of tree planting, would greatly restore connectivity of the landscape prior to the spruce budworm outbreak. Areas of high priority for tree planting outside the Park should be further analyzed prior to restoration to consider land ownership and physical access.

Important ecological considerations include what species are planted, where they are planted and how they are planted. The Park may aim to plant native spruce, balsam fir, white birch and potentially red maple trees as these commonly regenerate following insect outbreaks (Neily et al., 2010). In addition, boreal forest in Unama'ki is at its southern range limit. Climate change is expected to cause an increase in temperate, warm-adapted species in current coniferous dominant forests (Boulanger et al., 2017). These combined factors should be considered when selecting what species of trees to plant in areas identified as high priority for restoration. In addition, site specific conditions will need to be accounted for when determining exact tree planting sites. The present research incorporates data at a 30 m resolution, whereas site specific decisions must be made at a much finer scale and should incorporate soil conditions and neighbouring species. Finally, it is imperative that tree planting efforts are conducted with minimal impact to the ecosystem; this can be done by limiting creation of roads, planting diverse species as opposed to monocultures, avoiding the use of pesticides on trees, and implementing sustainable planting technique (Preece et al., 2023).

This research was focused to guide forest restoration specifically in CBHNP, however the results can be used in other applications and areas as well. Other protected area managers operating in Western Unama'ki (e.g., Mi'kmaw communities and representative organizations, towns, nature conservancies, and governments) could use the findings of this research to guide protected area establishment in areas of high priority for either connectivity or restoration. For example, the province of Nova Scotia has committed to protecting 20% of lands and waters by 2030 through the Environmental Goals and Climate Change Reductions Act (Environmental Goals and Climate Change Reduction Act, 2021), and the United Nations Convention on Biodiversity set a target of protecting

30% of land and waters by 2030 globally (Kunming - Montreal Global Biodiversity Framework: 2030 Targets, 2023). As of December 2021, protected areas in Unama'ki represent 19% of the landmass; this goes up to 33% in the study area itself. With only 29% considered crown land (NS DNRR, n.d.), Nova Scotia is largely privately owned and land trusts are effective mechanisms to acquire and protect private land. Locally, this includes the Nova Scotia Nature Trust, Nature Conservancy Canada and the Sespite'tmnej Kmitkinu Conservancy. These groups may wish to consider prioritizing connected forest stands when expanding their protected areas networks.

3.4.4 Limitations

Several limitations persist in the results presented here. The data provided by Parks Canada has not been validated outside the border of CBHNP. As such, model results outside the park boundary should be interpreted cautiously. However, for the purpose of guiding tree planting within CBHNP, the data and subsequent model results in the Park are likely sufficiently accurate.

As additionally shown through Table 3.3, the quality of the input data did not meet the positional accuracy and redundancy criterion. It is not uncommon for contemporary ecological analyses to use data at less than 1 m^2 accuracy (Auffret et al., 2015). The resolution of the forest cover data at 30 m^2 is considered coarse, and a finer resolution would ultimately provide a greater level of detail in the model outputs. However, it is worth noting that 30 m^2 resolution data for historical forest cover as far back as 1972 is rare. For example, both the Global Forest Watch (*Tree Cover Gain (2000-2012)*, 2019) and Hansen et al. (2013) analyse forest cover data at 30 m^2 resolution, only going back to 2000. Therefore, I argue that while a 30 m resolution dataset is coarse for present day analysis, it is accurate for 1972 and so can be considered as sufficiently informative. The redundancy criterion is a difficult measure to meet, as there is often only one dataset available to represent a feature, especially in the case of satellite data. Redundancy was not considered a critical factor and so did not prevent the use of these data in this analysis. In addition, the forest cover data was classified at the forest type level ('coniferous', 'deciduous', 'mixed', and 'disturbed'). Further classification down to the species level would also result in more detailed outputs. Understanding change in individual tree species composition and connectivity may be used to better understand impacts of forest connectivity loss to specific wildlife species dependent on a specific tree species and compositions.

When comparing high value areas (top 10%) in Figure 3.16 with the NS Forest Inventory, I found that the majority of high value areas occur in natural stands (42%) dominated by balsam fir (26%) and white spruce (20%; Table 3.10, Table 3.11). A natural stand is defined as "any forested stand which has not been treated silviculturally and does not qualify under clear cut, partial cut, burn, old field, wind throw, alders, brush or dead categories" (NS DNRR, 2016). This is despite the fact that the tree planting prioritization model (Figure 3.15) does not include areas of present day forest cover represented in the 2019 data provided by Parks Canada. This indicates that polygons claiming to contain natural stands in the NS Forest Inventory, are not considered forest stands in the forest cover data from Parks Canada. Visual analysis of natural stands in the NS Forest Inventory considered high value alongside satellite imagery shows that many of them in fact represent areas of logging. Furthermore, the NS Forest Inventory scored lower than the Parks Canada forest cover data in the data quality assessment (Table 3.3). Both findings lead me to use the NS Forest Inventory cautiously. It seems likely the NS Forest Inventory has either incorrectly identified these areas as natural stands or has not been updated since logging took place. I recommend that ground truthing of these stands be conducted to determine whether they in fact contain natural tree cover or have been disturbed in some way. Stands found to contain tree cover through ground truthing should be removed from the tree planting prioritization outputs as these areas would then not be suitable for tree planting.

The tree planting prioritization model highlights areas of key importance to forest density and connectivity. This analysis did not, however, account for any other biological, cultural, social, or economic values. It is advised that any forest management plan should incorporate these other perspectives. In addition, the output of this model is a starting point for guiding restoration work. Further ground-truthing and analysis of satellite imagery would better pinpoint exact locations suitable for tree planting and could include practical considerations such as distance to a road (access), elevation, etc.

Generally, Zonation software is built to prioritize large areas according to the parameters set by the user. It is not ideal for use in specific corridor analysis, wherein the user is interested in optimal movement pathways between existing patches of habitat. As this exercise was interested in overall structural connectivity and tree planting prioritization, this was not a limitation. However, further functional connectivity analyses considering individual species movement, or road network prioritization research, would benefit from a corridor connectivity analysis available through other software such as Circuitscape.

Finally, this present research is based on Western understandings of ecological connectivity. Future work would benefit greatly by learning from and incorporating Indigenous ways of understanding biocultural connectivity. For example, an Etuaptmumk (two-eyed seeing) approach combines the strengths of Indigenous and mainstream (Western) knowledge systems to co-produce knowledge (Marshall, 2004; Reid et al., 2020), and could be a further extension on this connectivity analysis. However it is imperative that co-produced research with Indigenous communities is conducted through a decolonial lens (Zurba et al., 2019). The OCAP® principles define the rights of Indigenous communities to their own data and knowledge and are a guide for engaging with Indigenous communities from within a settler, colonial institution such as academia (The First Nations Information Governance Centre, 2014). See Garnett et al. (2018), Jessen et al. (2022), Kadykalo et al. (2021), and M'sɨt No'kmaq et al. (2021) for discussions and evidence on the importance and benefits of valuing Indigenous knowledge in conservation research. Expansions on this research to include Indigenous knowledge should follow these examples and guidelines.

3.5 CONCLUSION

Chapter 3 examined three specific research objectives which will be summarized in turn. First, coniferous forest change prior to and following the SBW outbreak was calculated. As other researchers have noted, significant forest was lost immediately following the outbreak. Stands in protected areas were more heavily affected, with 48% of coniferous forest lost between 1972 and 1989 in protected areas, compared to 41% outside protected areas (Figure 3.4). Further, mean coniferous stand area (df = 4, F = 18.77, $p \leq 0.001$) and perimeter (df = 4, F = 21.02, $p \leq 0.001$) was larger in 1972 compared to all subsequent time steps. Normalized perimeter index, a calculation of the relationship between area and perimeter, was consistently larger in subsequent time steps than in 1972 ($p<0.05$), aside from 2009, indicating a trend towards less convoluted shapes of forest stands.

Individual models prioritizing connectivity of coniferous forest stands were produced for all time steps (Figure 3.9). In 1972, approximately half of all high value areas (top 10%) were found in protected areas, with 26 % located specifically in CBHNP (Table 3.9). This proportion drops between 1972 and 1989 and continues to steadily decline until the proportion remaining in 2019 in protected is about 21% and 2.5% in CBHNP (Table 3.9). To put this in context, protected areas cover about 33% of landmass in the study area and CBHNP 17%. Therefore, prior to the SBW outbreak, protected areas represented a disproportionately large amount of high value for connectivity stands, and a considerably lower proportion in 2019. Figure 3.11 helps visualize where coniferous stand value has increased or decreased between time steps and an overall analysis of present day forest connectivity (including all 2019 forest types and non-forest) is shown in Figure 3.12.

Finally, areas of high priority for tree planting, based on historical and present day connectivity, were identified. A model of restoration opportunity, based on presence and connectivity of historical forest cover, present day forest cover and non-forest areas was produced. I edited the output to remove areas that presently contain forest cover because non forested areas will be the focus of tree planting. Of the top 10% value non forest areas, 60% were located in protected areas and 36% were in CBHNP. This is likely due to the concentration of high value cells in the Park (26%) and in protected areas (50%) in 1972 (Table 3.9). We can therefore be confident that the high priority areas are capturing stands which, if were the focus of tree planting, would greatly restore connectivity of the landscape prior to the spruce budworm outbreak.

The prioritization algorithm in Zonation software has previously been used in a variety of decision making processes, including conservation planning for terrestrial (Albert et al., 2017; Lehtomäki et al., 2009) and marine habitat (Allnutt et al., 2012), under anticipated climate change scenarios (Carroll et al., 2010) and to guide forest management (Robinne et al., 2020; Westwood et al., 2020). The models produced here could be used by any land manager or decision maker considering landscape connectivity in Unama'ki. However, there are no known studies that use Zonation to guide forest restoration efforts based on historical forest connectivity. While this research will support conservation activity in Unama'ki, it also proves the effectiveness of this spatial prioritization approach in forest restoration work broadly.

While the analysis on forest loss and connectivity presented here provide valuable information to land managers, further research questions remain. For example, a connectivity model could be created with data for various non-tree species of interest. Occurrence or distribution data for at-risk Bicknell's thrush, Canada lynx and American marten could be included, so that forest that is considered connected to these species' habitat is prioritized. Such an output could guide species at risk management efforts in tandem with forest restoration. This would shift the model to include a functional connectivity component and the final prioritization would therefore vary depending on the species included. Furthermore, although biodiversity data collection and analysis in recent decades has been heavily focused on at-risk species (Boakes et al., 2010), it is recommended that further studies not only include species at risk, but also include culturally significant species to the Mi'kmaq of Unama'ki. In addition, one of the flexibilities of Zonation as an analysis approach is that it can consider not only species distribution information, but also the distribution of economic, social, and cultural factors and can produce informative comparison scenarios. For example, future research questions could include how the restoration of presently identified high priority areas would affect connectivity of old growth forest, or of culturally significant areas. One could add a land ownership feature to prioritize conservation on publicly owned land, or to identify high value private land.

CHAPTER 4 CONCLUSION

This thesis presents the first attempt to model historical forest cover data in Zonation software to guide tree planting. It is well known that intact, healthy forest ecosystems are vital to the sustainable function of nature. Boreal forests particularly help sequester carbon, regulate water cycles, control erosion, provide key habitat and are interconnected with many Indigenous communities. Efforts to protect intact boreal forest must be prioritized. In cases where forest has already been disturbed, restoration is necessary. This thesis is one of many steps to ensure that desired boreal forest restoration work in Unama'ki is conducted efficiently.

It is vital that stakeholders understand the reliability of data upon which a model is built, in order to responsibly make decisions. The data quality assessment tool presented in Chapter 2 is a simple, comprehensive approach to calculating and communicating spatial data quality to both model builders and end users. The output of the tool is a table of criteria that a dataset does and does not meet, as well as a total tally of what criteria were met. The tool can be easily interpreted by end-users, can contextualize the results of a model and delineate its limitations, can be used to guide data inclusion and cleaning decisions, and can be used to inform future data collection efforts. It is recommended that other researchers implement the approach to examine whether there are modelling contexts in which the tool is not applicable. Otherwise, the simplicity and flexibility of the tool may make its use in many model and planning situations valuable.

Chapter 3 examined three specific research objectives which will be summarized in turn. First, coniferous forest change prior to and following the SBW outbreak was calculated. As other researchers have noted, significant forest was lost immediately following the outbreak, and many stands were unable to regenerate due to over browsing by the hyperabundant moose population. Stands in protected areas were more heavily affected, with 48% of coniferous forest lost between 1972 and 1989 in protected areas, compared to 41% outside protected areas (Figure 3.4). Further, mean coniferous stand area (df = 4,

$F = 18.77$, $p \leq 0.01$) and perimeter ($df = 4$, $F = 21.02$, $p \leq 0.01$) was larger in 1972 compared to all subsequent time steps. Normalized perimeter index, a calculation of the relationship between area and perimeter, was consistently larger in all subsequent time steps than in 1972 ($p < 0.05$), aside from 2009, indicating a trend towards less convoluted shapes of forest stands.

Individual models prioritizing connectivity of coniferous forest stands were produced for all time steps (Figure 3.9). In 1972, approximately half of all high value areas (top 10%) were found in protected areas, with 26 % located specifically in CBHNP (Table 3.9). This proportion drops between 1972 and 1989 and continues to steadily decline until the proportion remaining in 2019 in protected is about 21% and 2.5% in CBHNP (Table 3.9). To put this in context, protected areas cover about 33% of landmass in the study area and CBHNP 17%. Therefore, prior to the SBW outbreak, protected areas represented a disproportionately large amount of high value stands. Figure 3.11 helps visualize where coniferous stand value has increased or decreased between time steps and an overall analysis of present-day forest connectivity (including all 2019 forest types and non-forest) is shown in Figure 3.12.

Finally, I identified areas of high priority for ecological restoration through tree planting based on historical and present day connectivity. A model of restoration opportunity, based on presence and connectivity of historical forest cover, present day forest cover and non-forest areas was produced. I analyzed the output to remove areas that presently contain forest cover because these will be the focus of tree planting. Of the top 10% value areas, 60% were located in protected areas and 36% were in CBHNP. This is likely due to the concentration of high value cells in the Park (26%) and in protected areas (50%) in 1972 (Table 3.9). We can therefore be confident that the high priority areas are capturing stands which, if were the focus of tree planting, would greatly restore connectivity of the landscape prior to the spruce budworm outbreak.

I reiterate that countless studies have shown that biodiversity hotspots, key habitat and at-risk species are located on Indigenous land (Fernández-Llamazares et al., 2021; O'Bryan et al., 2021; Renwick et al., 2017) Indigenous communities have embedded in their culture local ecological knowledge about how to sustainably manage and live in harmony with nature (Berkes et al., 2000; Charnley et al., 2007; Joa et al., 2018; Reyes-García et al., 2022). Given the time constraints of a Master's thesis and the importance of long-term relationship for respectful, coproduced research between settler and Indigenous peoples (Saturno et al., 2023; Westwood, Barker, et al., 2020), I did not include Indigenous knowledge into the research presented herein. However, I wish to conclude on the note that all academic research should seek to understand the impact and potential benefits it may have to local Indigenous communities. The Mi'kmaq have stewarded these lands since time immemorial and as a settler Treaty person in Turtle Island, I recognize my responsibility to act in accordance with Truth and Reconciliation. I am hopeful this work can be of use to the Mi'kmaq Peoples interested in boreal forest connectivity and conservation in Unama'ki.

Based on UNDRIP and the Treaties of Peace and Friendship, the Mi'kmaq have rights to self-determination on their lands. Although by Canadian statutes, the Crown and private landowners have control over their own lands (so long as they adhere to all laws and regulations), in the quest for reconciliation with Indigenous peoples and the respect of UNDRIP and the Treaties, I recommend that any treeplanting or restoration based on this research engage Indigenous community members, including knowledge-holders, elders, and youth. In addition, future research and management should be coproduced and cogoverned with Mi'kmaw communities and their representative organizations.

The models produced here could be used by any land manager or decision maker considering boreal forest connectivity in Unama'ki to supplement land management decision making. However, there are no known studies that use Zonation to guide forest restoration efforts based on historical forest loss. While this research will support conservation activity in Unama'ki, it also proves the effectiveness of this spatial prioritization approach in restoration work broadly.

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APPENDIX A DESCRIPTION OF FIELDS IN NS FOREST INVENTORY

Table B.1 Description of Fornon fields in NS Forest Inventory (NS DNRR, 2021) used in analysis. Definitions taken from metadata (NS DNRR, 2016).

Field value	Definition
0	Natural stand - any forested stand which has not been treated silviculturally and does not qualify under clear cut, partial cut, burn, old field, wind throw, alders, brush or dead categories
1	Treated - treatment not classified, an area where silviculture activity has occurred, but the actual treatment is not identified in field data from other Department programs. This treatment excludes stands that are defined by other forest codes, such as plantations, Christmas trees, sugar bush, etc.
9	Dead - 2 - Any stand that contains dead trees greater than 5 meters due to any cause and which contains 51-75% crown closure of live residual material (or 25 to 49 % of dead material) and which contains evidence of dead material either standing or laying on the ground with little or no evidence of regeneration. If a portion of the stand with dead material is contiguous then a new stand can be created if the area is a hectare or more in size. All normal attributes are assigned to the live residual material. Stands with less than 15% of dead material are to be classed as a natural forest stand.
12	Treated stand - treatment classified-an area where silviculture activity has occurred, and the actual treatment has been identified primarily by field data from other Department programs. This treatment excludes stands that are defined by other forest codes, such as plantations, Christmas trees, sugar bush etc.
16	Moose Meadow - Any stand solely found in the Cape Breton highlands with the appearance of old field returning to forest. Generally white spruce will be the only commercial species present with a crown closure less than 25%. All normal attributes are assigned to the existing commercial tree species as the main story. There can be no second story.
20	Plantation – A group of trees artificially established by direct seeding or setting out seedlings, transplants or cuttings.

Field value	Definition
60	Clear cut - Any stand that has been completely cut and any residuals make up less than 25% crown closure and with little or no indication of regeneration. Site values are retained. Residual live commercial material is described as the second story
70	Wetlands general - Any wet area, not identified as a lake, river or stream, excluding open and treed bogs, and beaver flowage. (In the Interpreted Forest Inventory Database, wetland complexes may include open and treed bogs).
71	Beaver flowage - Any area that is or has been occupied by beavers. No Forest information is provided for these areas (i.e., site, height, species, crown closure) as this designation refers only to the water flowage area or may be for grassy areas created by the beaver dam.
72	Open bogs - Any area consisting primarily of ericaceous plants, sphagnum or other mosses with less than 25% live tree cover and poor drainage and wet all year. Indicator plants: Bog Rosemary, Leather Leaf, Labrador Tea, Cranberry and Lambkill. Ericaceous plants being plants in or related to the heather family (*ericaceae*). They are typically plants indicative of acid soils, bogs and woodlands.
73	Treed bogs - Any area consisting primarily of ericaceous plants, sphagnum or other mosses with stunted softwood or hardwood species having 25% or more live tree cover
74	Ocean Wetland - Ocean water portion of a wetland.
75	Wetland In Lake - Lake water portion of a wetland.
76	Cliffs, dunes, coastal rocks – the area of land between the high tide mark and the forest or non-forest stand and consists of cliffs (a high steep face of a rocky or soil mass), dunes (a ridge or hill created by windblown sand), or coastal rock (a toque shaped or lobate area of bedrock, may or may not extend into the water).
77	Inland water - May include lakes, rivers, reservoirs, canals and ponds (STAND_ value: 9003)

Field value	Definition
78	Ocean - Any area of salt water beyond harbour mouths as indicated by virtual boundaries assigned as part of original interpretation. (STAND_ value of 9006)
84	Rock barren - Any area covered by at least 50% exposed rock outcrop and/or boulders with less than 25% live tree cover. (Boulders being rock fragments over 60cm in diameter.)
85	Barren - Any area of less than 25% live tree cover containing "ericaceous" vegetation with less than 50% rock out crops and/or boulder cover and less than 50% other woody plant cover. Area is dry and firm in summer. Indicator plants: Bearberry, Rhodora, Blueberry, Huckleberry and Lambkill.
86	Agriculture - Any hay field, pasture, tilled crop, or orchard which contains no merchantable tree species.
87	Urban - Any area used primarily as residential, industrial and related structures such as streets, sidewalks, parking lots, etc. Also includes house lots in wooded areas outside of towns and villages which are not adjacent to agricultural land and those lots surrounded by forest will have to be delineated according to these specifications. In cases of ribbon development along some roads then a strip may be delineated along the road and coded accordingly. Obvious urban area within agricultural land will be delineated and coded accordingly. Ribbon development pertains to the unplanned rural housing that occurs along roads. Categories that will be classified as urban are bunkers, golf courses, picnic parks, campgrounds, drive in theaters, auto salvage yards, power stations, water treatment areas, lagoons sewer/water, cemeteries, light houses, ball parks, etc.
91	Blueberries - Areas that appear to have been or are being used for commercial blueberry production.
92	Miscellaneous - Any non-forest land not covered by the listed FORNON codes.
93	Sanitary land fill - Areas used by municipalities for disposal of garbage by means of burying the material not usually included in an Urban area.
94	Beach - That area of land between normal water line and the forest or non-forest category (i.e., bog, etc.). Area showing due to abnormally low water is not considered to be part of a beach.
95	Gravel pit - Any area either active or non-active used for the purpose of extracting gravel.

Field value	Definition
97	Powerline corridor – A powerline corridor identifiable on a 1:12,500 scale aerial photograph. (STAND_ value 9002)
98	Road corridor - Generated polygons of varying widths for paved and two-lane roads. (STAND_ value 9000)
99	Rail corridor - Generated 20 meter polygons around active and abandoned rail lines (STAND_ values 9001 & 9005)

APPENDIX B VISUALIZATION OF VARYING DISPERSAL KERNEL INFLUENCE ON CONNECTIVITY MODELS

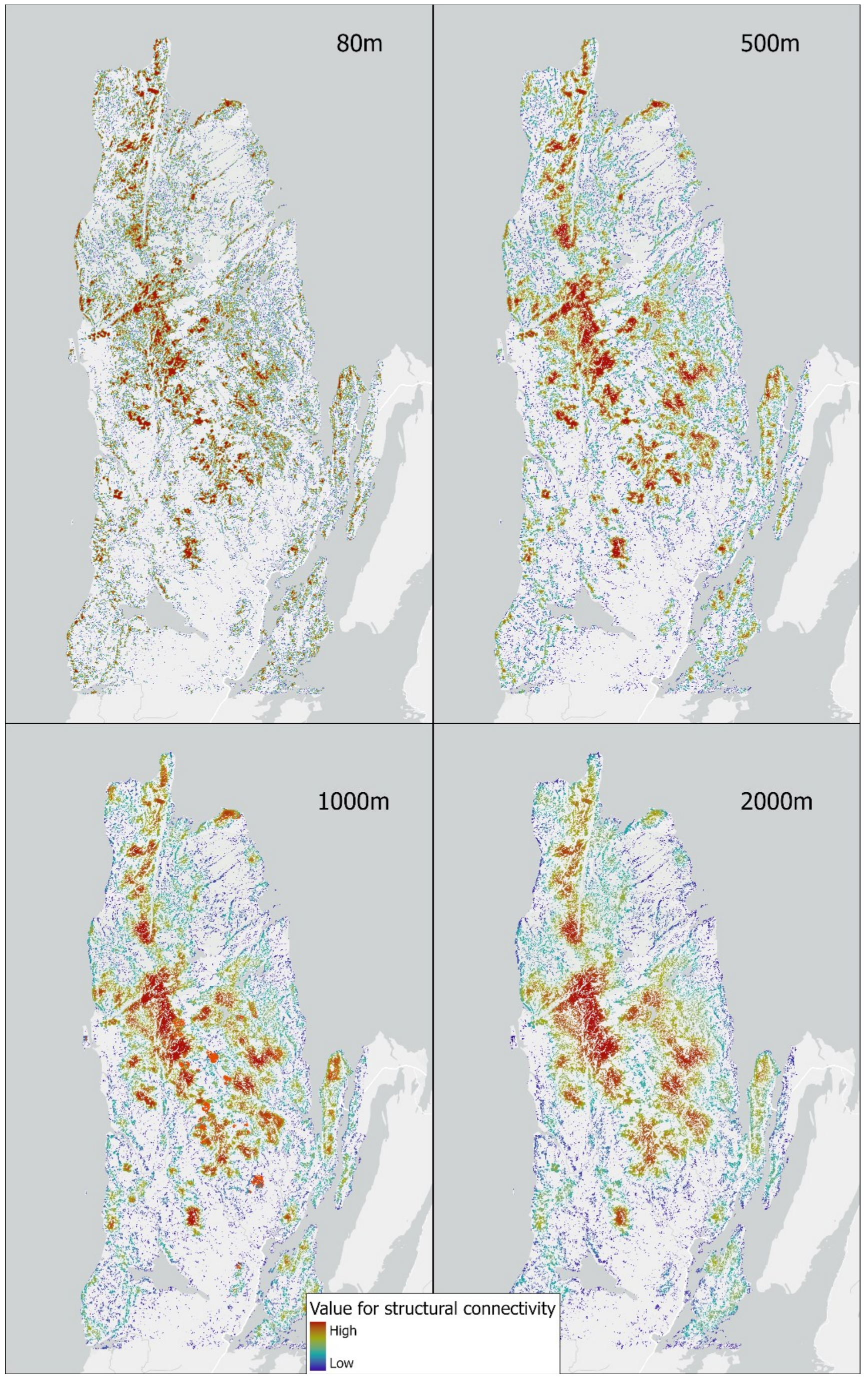

Figure A.1 Models of structural connectivity of coniferous forest in 1972 using four different dispersal kernels: 80m, 500m, 1000m, 2000m.

APPENDIX C STATISTICS OF FOREST COVER CHANGE

Table C.1 One-way ANOVA of mean coniferous stand area for all time steps (1972, 1989, 1999, 2009 and 2019).

	Sum of Squares	df	Mean Square	F	Significance
Between Groups	2.67E+12	4	6.66E+11	19.57	<0.001
Within Groups	1.18E+16	346078	3.40E+10		
Total	1.18E+16	346082			

Table C.2 One-way ANOVA of mean coniferous forest stand perimeter for all time steps (1972, 1989, 1999, 2009,2019).

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	938,844,891	4	234,711,222.70	21.94	<0.01
Within Groups	3.70E+12	346,078	10,696,014.97		
Total	3.70E+12	346,082			

Table C.3 One-way ANOVA of mean coniferous stand normalized perimeter index for all time steps (1972, 1989, 1999, 2009, 2019).

	Sum of Squares	df	Mean Square	F	Significance
Between Groups	1.54	4	0.385	18.124	<0.01
Within Groups	7353.16	346078	0.021		
Total	7354.70	346082			

Table C.4 Post hoc test of one-way ANOVA of mean area of coniferous forest stands between time steps.

Post hoc test	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.*	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	1972	1989	7751.6*	988.78	0.000	5054.46	10448.84
		1999	6698.3*	1008.47	0.000	3947.39	9449.16
		2009	6164.9*	1012.13	0.000	3404.04	8925.80
		2019	5413.6*	1012.13	0.000	2652.69	8174.45
	1989	1972	-7751.6*	988.78	0.000	-10448.84	-5054.46
		1999	-1053.4	1014.21	0.837	-3819.93	1713.16
		2009	-1586.7	1017.85	0.524	-4363.22	1189.75
		2019	-2338.1	1017.85	0.146	-5114.57	438.40
	1999	1972	-6698.3*	1008.47	0.000	-9449.16	-3947.39
		1989	1053.4	1014.21	0.837	-1713.16	3819.93
		2009	-533.3	1036.98	0.986	-3362.03	2295.32
		2019	-1284.7	1036.98	0.729	-4113.38	1543.98
	2009	1972	-6164.9*	1012.13	0.000	-8925.80	-3404.04
		1989	1586.7	1017.85	0.524	-1189.75	4363.22
		1999	533.3	1036.98	0.986	-2295.32	3362.03
		2019	-751.3	1040.55	0.951	-3589.75	2087.05

Post hoc test	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.*	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
	2019	1972	-5413.5*	1012.13	0.000	-8174.45	-2652.69
		1989	2338.1	1017.85	0.146	-438.40	5114.57
		1999	1284.7	1036.98	0.729	-1543.98	4113.38
		2009	751.4	1040.55	0.951	-2087.05	3589.75
Bonferroni	1972	1989	7751.6*	988.78	0.000	4976.09	10527.22
		1999	6698.3*	1008.47	0.000	3867.45	9529.09
		2009	6164.9*	1012.13	0.000	3323.81	9006.03
		2019	5413.6*	1012.13	0.000	2572.46	8254.68
	1989	1972	-7751.6*	988.78	0.000	-10527.22	-4976.09
		1999	-1053.4	1014.21	1.000	-3900.32	1793.55
		2009	-1586.7	1017.85	1.000	-4443.90	1270.43
		2019	-2338.1	1017.85	0.216	-5195.25	519.08
	1999	1972	-6698.3*	1008.47	0.000	-9529.09	-3867.45
		1989	1053.4	1014.21	1.000	-1793.55	3900.32
		2009	-533.3	1036.98	1.000	-3444.22	2377.52
		2019	-1284.7	1036.98	1.000	-4195.57	1626.17
	2009	1972	-6164.9*	1012.13	0.000	-9006.03	-3323.81
		1989	1586.7	1017.85	1.000	-1270.43	4443.90
		1999	533.4	1036.98	1.000	-2377.52	3444.22

Post hoc test	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.*	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
	2019	2019	-751.3	1040.55	1.000	-3672.22	2169.53
		1972	-5413.6*	1012.13	0.000	-8254.68	-2572.46
		1989	2338.1	1017.85	0.216	-519.08	5195.25
		1999	1284.7	1036.98	1.000	-1626.17	4195.57
		2009	751.3	1040.55	1.000	-2169.53	3672.22

*. The mean difference is significant at the 0.05 level.

Table C.5 Post hoc test of one-way ANOVA of mean perimeter of coniferous forest stands between time steps.

Post hoc test	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.*	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Tukey HSD	1972	1989	144.9*	17.5	0.000	97.11	192.65
		1999	126.1*	17.9	0.000	77.37	174.82
		2009	115.5*	17.9	0.000	66.64	164.44
		2019	102*	17.9	0.000	53.09	150.89
	1989	1972	-144.9*	17.5	0.000	-192.65	-97.11
		1999	-18.8	18	0.834	-67.79	30.22
		2009	-29.3	18	0.480	-78.52	19.84
		2019	-42.8	18	0.121	-92.07	6.29
	1999	1972	-126.1*	17.9	0.000	-174.82	-77.37
		1989	18.8	18	0.834	-30.22	67.79
		2009	-10.6	18.4	0.979	-60.66	39.55
		2019	-24.1	18.48	0.683	-74.21	26.00
	2009	1972	-115.5*	17.9	0.000	-164.44	-66.64
		1989	29.3	18	0.480	-19.84	78.52
		1999	10.6	18.4	0.979	-39.55	60.66
		2019	-13.5	18.4	0.948	-63.82	36.72

Post hoc test	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.*	95% Confidence Interval	
						Lower Bound	Upper Bound
Bonferroni	2019	1972	-102*	17.9	0.000	-150.89	-53.09
		1989	42.9	18.0	0.121	-6.29	92.07
		1999	24.1	18.4	0.683	-26.00	74.21
		2009	13.5	18.4	0.948	-36.72	63.82
	1972	1989	144.9*	17.5	0.000	95.72	194.04
		1999	126.1*	17.9	0.000	75.95	176.23
		2009	115.5*	17.9	0.000	65.22	165.86
		2019	102*	17.9	0.000	51.67	152.31
	1989	1972	-144.9*	17.5	0.000	-194.04	-95.72
		1999	-18.8	18.0	1.000	-69.21	31.64
		2009	-29.3	18.0	1.000	-79.95	21.26
		2019	-42.9	18.0	0.174	-93.50	7.72
	1999	1972	-126.1*	17.9	0.000	-176.23	-75.95
		1989	18.8	18.0	1.000	-31.64	69.21
		2009	-10.6	18.4	1.000	-62.11	41.00
		2019	-24.1	18.4	1.000	-75.66	27.45
	2009	1972	-115.5*	17.9	0.000	-165.86	-65.22

Post hoc test	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.*	95% Confidence Interval	
						Lower Bound	Upper Bound
		1989	29.3	18.0	1.000	-21.26	79.95
		1999	10.6	18.4	1.000	-41.00	62.11
		2019	-13.5	18.4	1.000	-65.28	38.19
	2019	1972	-102*	17.9	0.000	-152.31	-51.67
		1989	42.9	18.0	0.174	-7.72	93.50
		1999	24.1	18.4	1.000	-27.45	75.66
		2009	13.5	18.4	1.000	-38.19	65.28

*. The mean difference is significant at the 0.05 level.

Table C.6 Post hoc test of one-way ANOVA of mean perimeter of coniferous forest stands between time steps.

Post hoc test	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Tukey HSD	1972	1989	-.00593*	0.00077	0.000	-0.008	-0.004
		1999	-.00293*	0.00079	0.002	-0.005	-0.001
		2009	-0.00196	0.00079	0.094	-0.004	0.000
		2019	-.004735*	0.00076	0.000	-0.007	-0.003
	1989	1972	.00592*	0.00077	0.000	0.004	0.008
		1999	.00300*	0.00079	0.001	0.001	0.005
		2009	.003967*	0.00079	0.000	0.002	0.006
		2019	0.00119	0.00077	0.528	-0.001	0.003
	1999	1972	.00293*	0.00079	0.002	0.001	0.005
		1989	-.00300*	0.00079	0.001	-0.005	-0.001
		2009	0.00097	0.00081	0.752	-0.001	0.003
		2019	-0.00180	0.00078	0.144	-0.004	0.000
	2009	1972	0.00196	0.00079	0.094	0.000	0.004
		1989	-.003967*	0.00079	0.000	-0.006	-0.002
		1999	-0.00097	0.00081	0.752	-0.003	0.001

Post hoc test	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Bonferroni	2019	2019	-.00277*	0.00079	0.004	-0.005	-0.001
		1972	.00473*	0.00076	0.000	0.003	0.007
		1989	-0.00119	0.00077	0.528	-0.003	0.001
		1999	0.00180	0.00078	0.144	0.000	0.004
	1972	2009	.00277*	0.00079	0.004	0.001	0.005
		1989	-.00593*	0.00077	0.000	-0.008	-0.004
		1999	-.00293*	0.00079	0.002	-0.005	-0.001
		2009	-0.00196	0.00079	0.130	-0.004	0.000
	1989	2019	-.00473*	0.00076	0.000	-0.007	-0.003
		1972	.00593*	0.00077	0.000	0.004	0.008
		1999	.00300*	0.00079	0.002	0.001	0.005
		2009	.00397*	0.00079	0.000	0.002	0.006
	1999	2019	0.00119	0.00077	1.000	-0.001	0.003
		1972	.002932*	0.00079	0.002	0.001	0.005
		1989	-.00300*	0.00079	0.002	-0.005	-0.001
		2009	0.00097	0.00081	1.000	-0.001	0.003
		2019	-0.00180	0.00078	0.214	-0.004	0.000

Post hoc test	(I) Year	(J) Year	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
	2009	1972	0.00196	0.00079	0.130	0.000	0.004
		1989	-.00396*	0.00079	0.000	-0.006	-0.002
		1999	-0.00097	0.00081	1.000	-0.003	0.001
		2019	-.00277*	0.00079	0.004	-0.005	-0.001
	2019	1972	.00473*	0.00076	0.000	0.003	0.007
		1989	-0.00119	0.00077	1.000	-0.003	0.001
		1999	0.00180	0.00078	0.214	0.000	0.004
		2009	.00277*	0.00079	0.004	0.001	0.005

*. The mean difference is significant at the 0.05 level.

APPENDIX D INDIVIDUAL MAPS OF CONIFEROUS FOREST TOTAL CHANGE BETWEEN 1972 AND SUBSEQUENT TIME STEPS

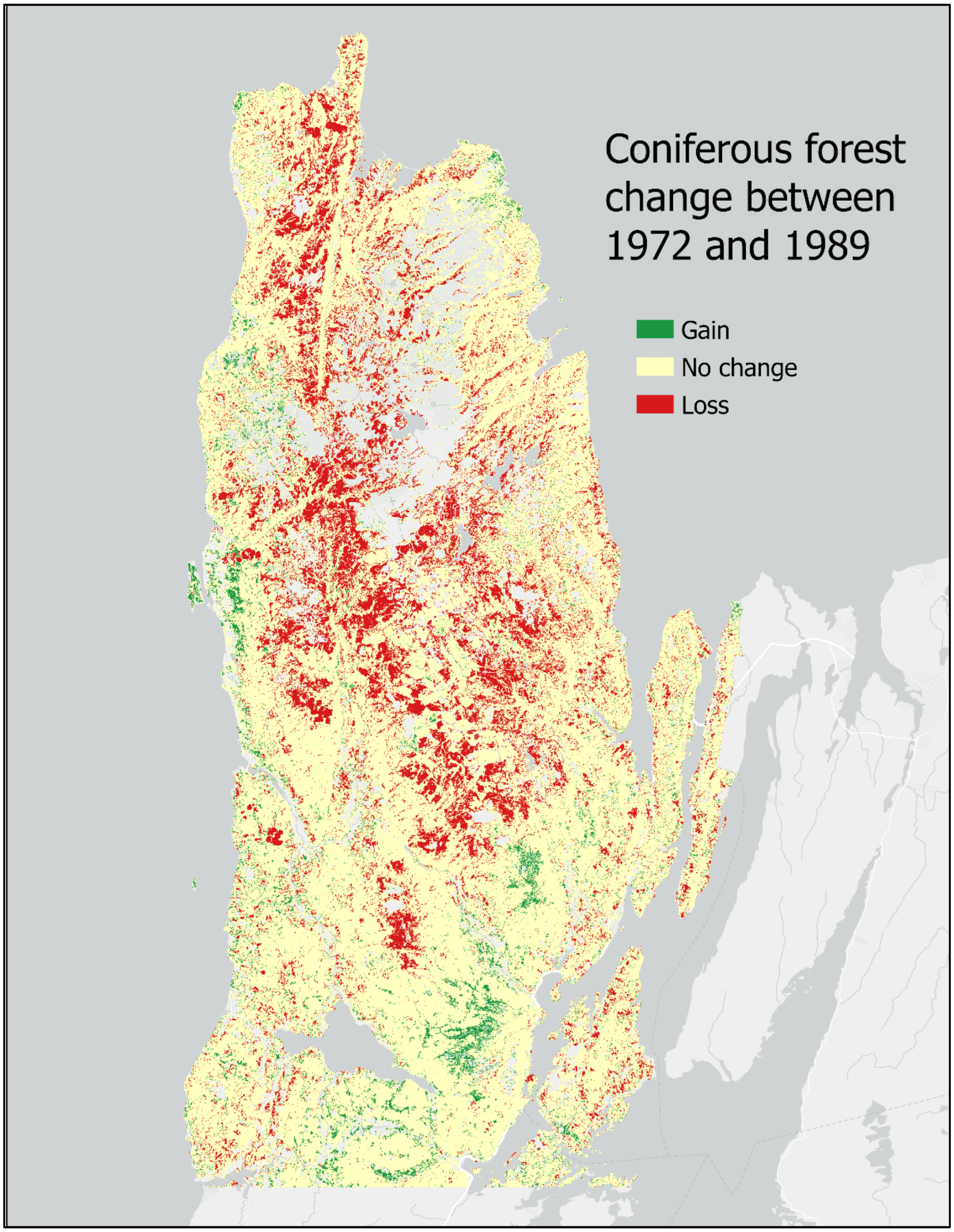

Figure E.1 Coniferous forest change between 1972 and 1989. Areas in green indicate stands that converted to coniferous forest between the two time steps, while red indicates areas where coniferous forest was lost and converted to another landcover type.

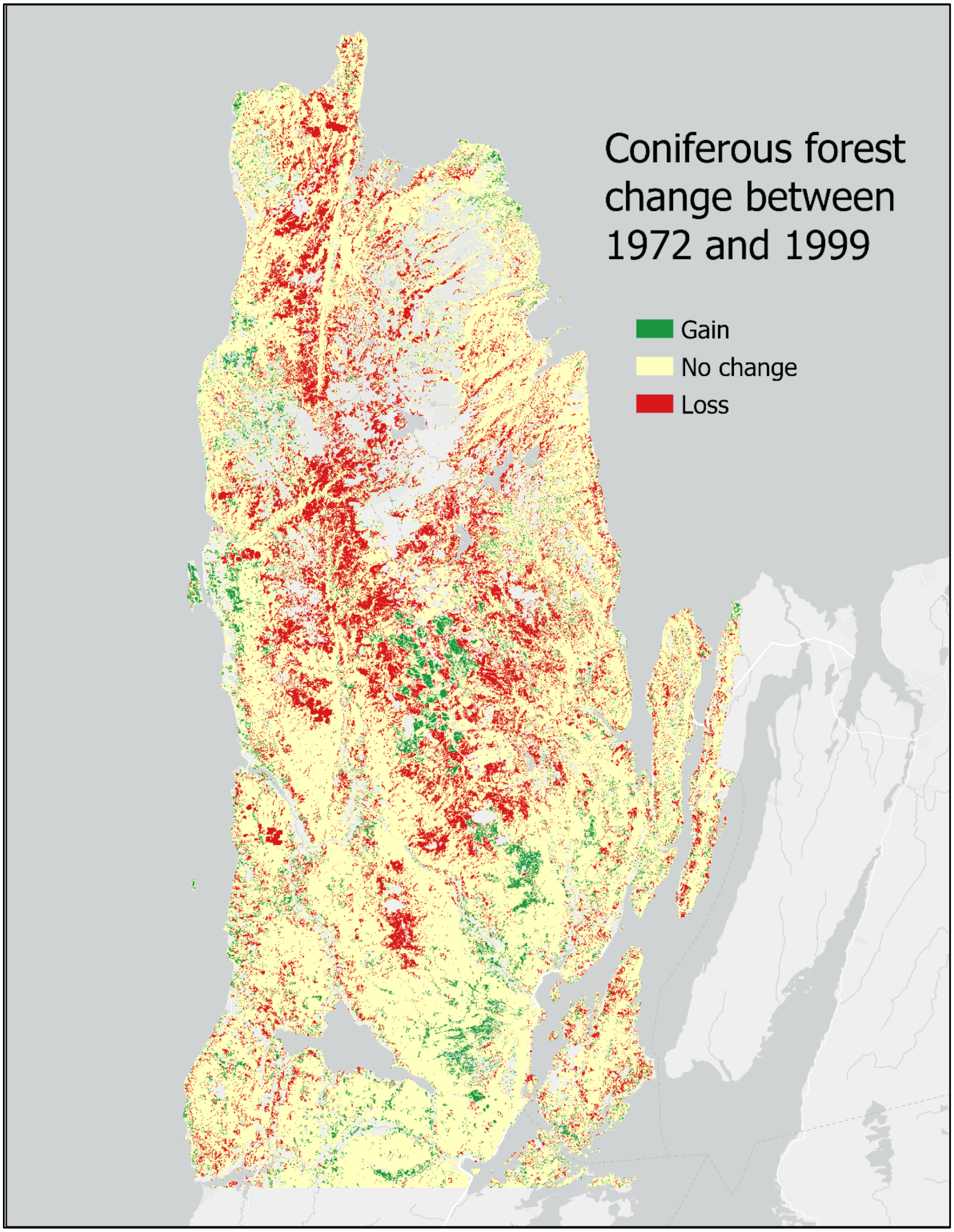

Figure E.2 Coniferous forest change between 1972 and 1999. Areas in green indicate stands that converted to coniferous forest between the two time steps, while red indicates areas where coniferous forest was lost and converted to another landcover type.

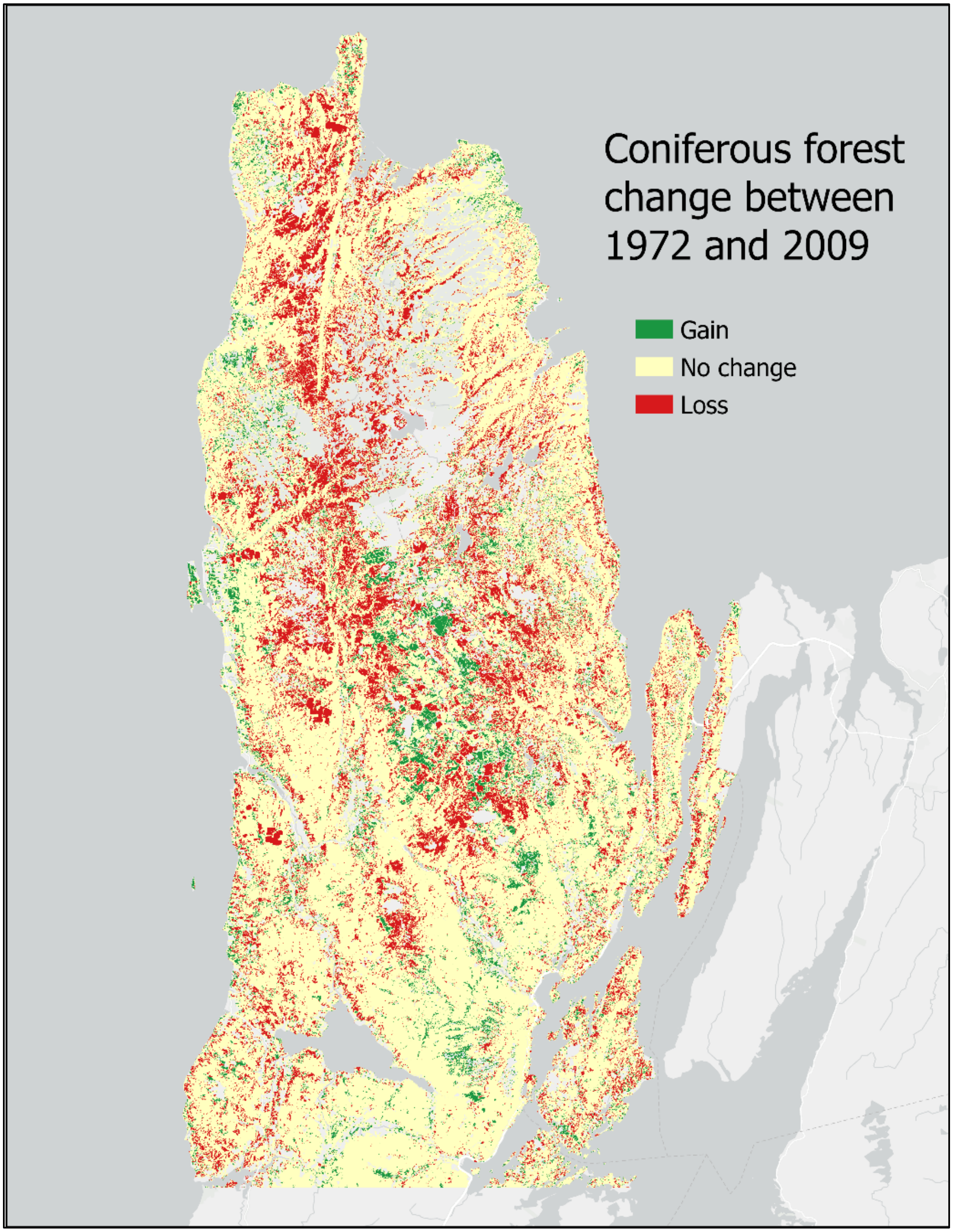

Figure E.3 Coniferous forest change between 1972 and 2009. Areas in green indicate stands that converted to coniferous forest between the two time steps, while red indicates areas where coniferous forest was lost and converted to another landcover type.

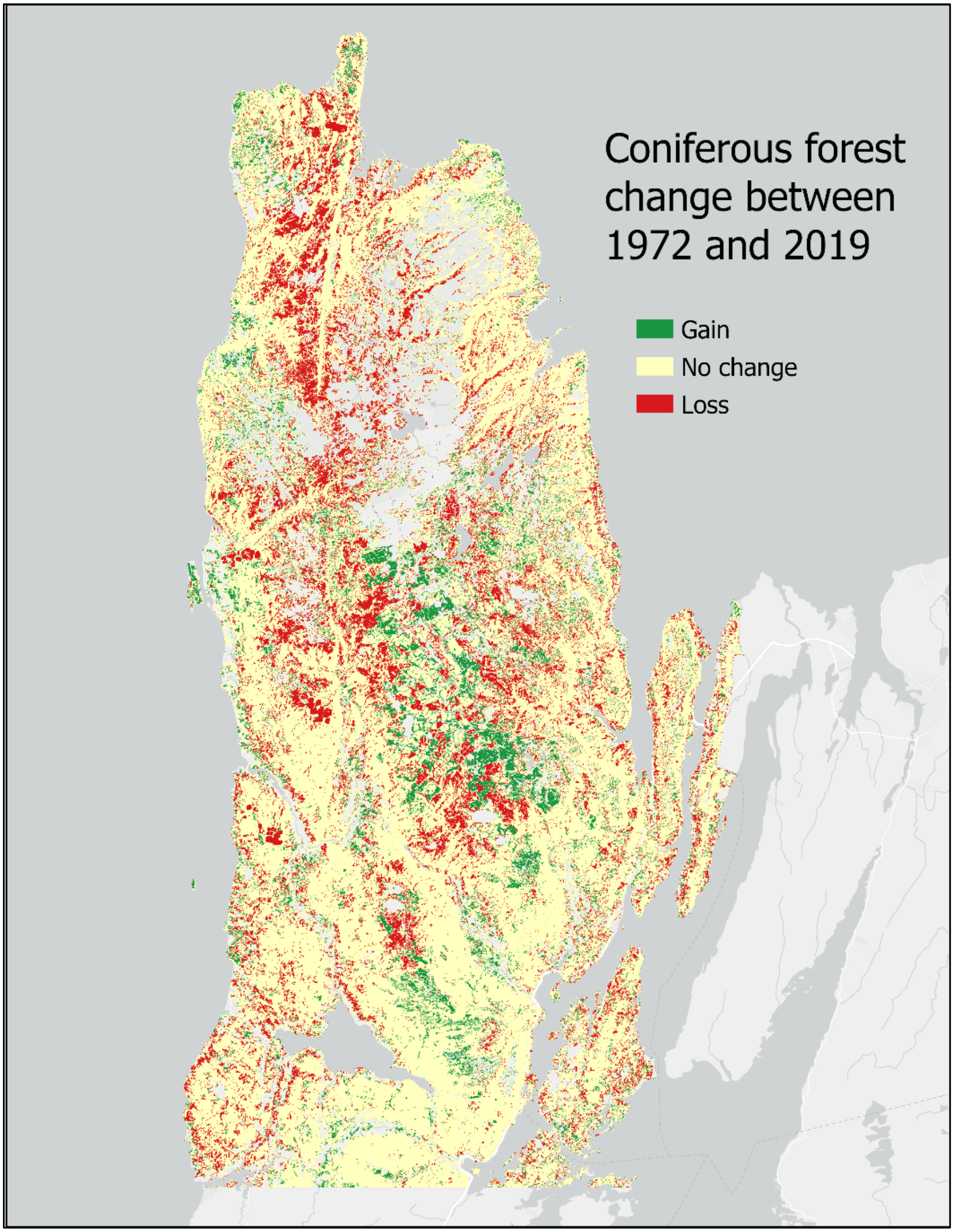

Figure E.4 Coniferous forest change between 1972 and 2019. Areas in green indicate stands that converted to coniferous forest between the two time steps, while red indicates areas where coniferous forest was lost and converted to another landcover type.

APPENDIX E CHANGE IN MEAN AND TOTAL CONIFEROUS FOREST STAND AREA AND PERIMETER PER SQUARE KM

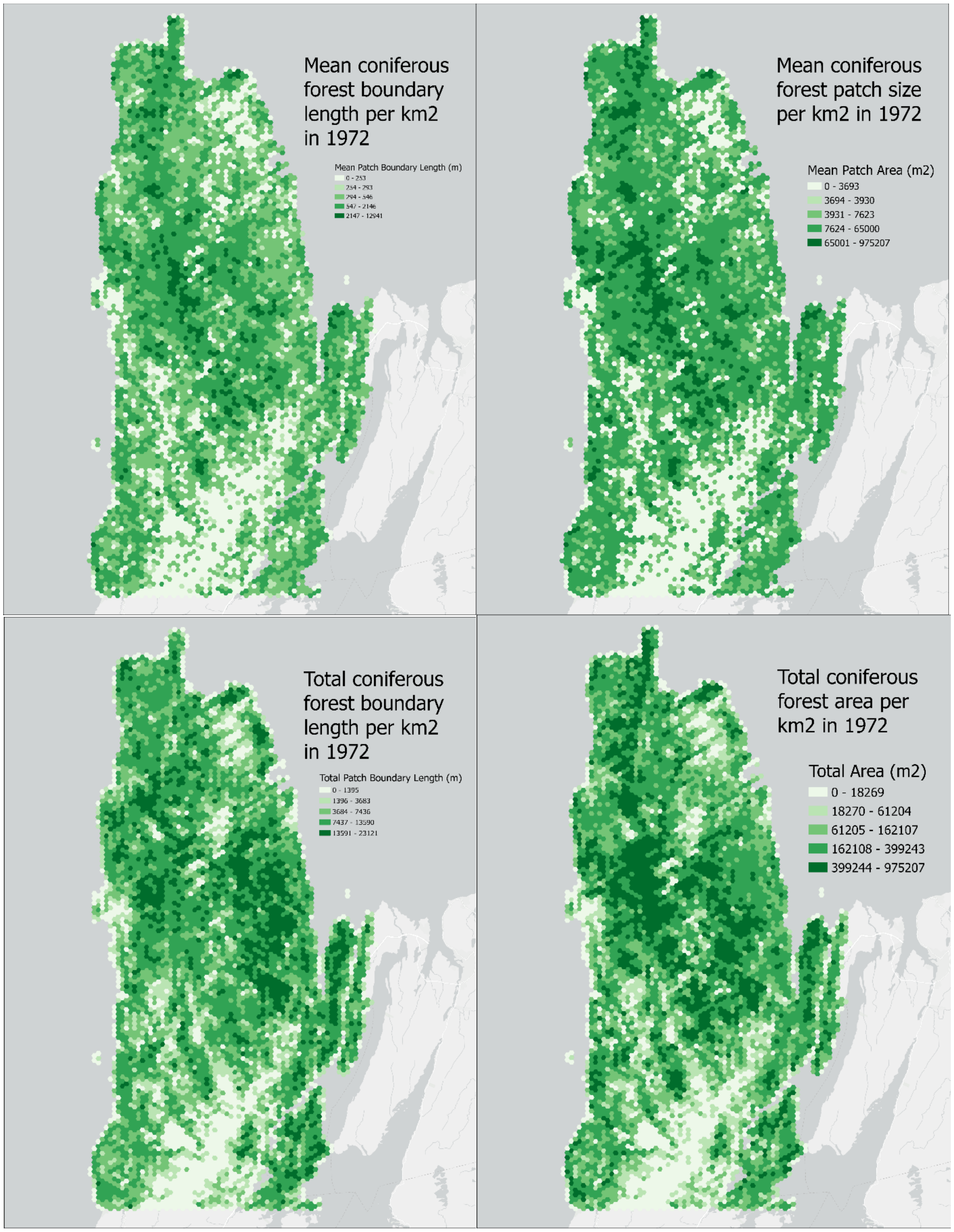

Figure D.1 Analysis of forest cover per km: mean stand boundary length (perimeter) and area; and total stand boundary length (perimeter) and area for 1972.

Figure D. 2 Analysis of forest cover per km: mean stand boundary length (perimeter) and area; and total stand boundary length (perimeter) and area for 1989.

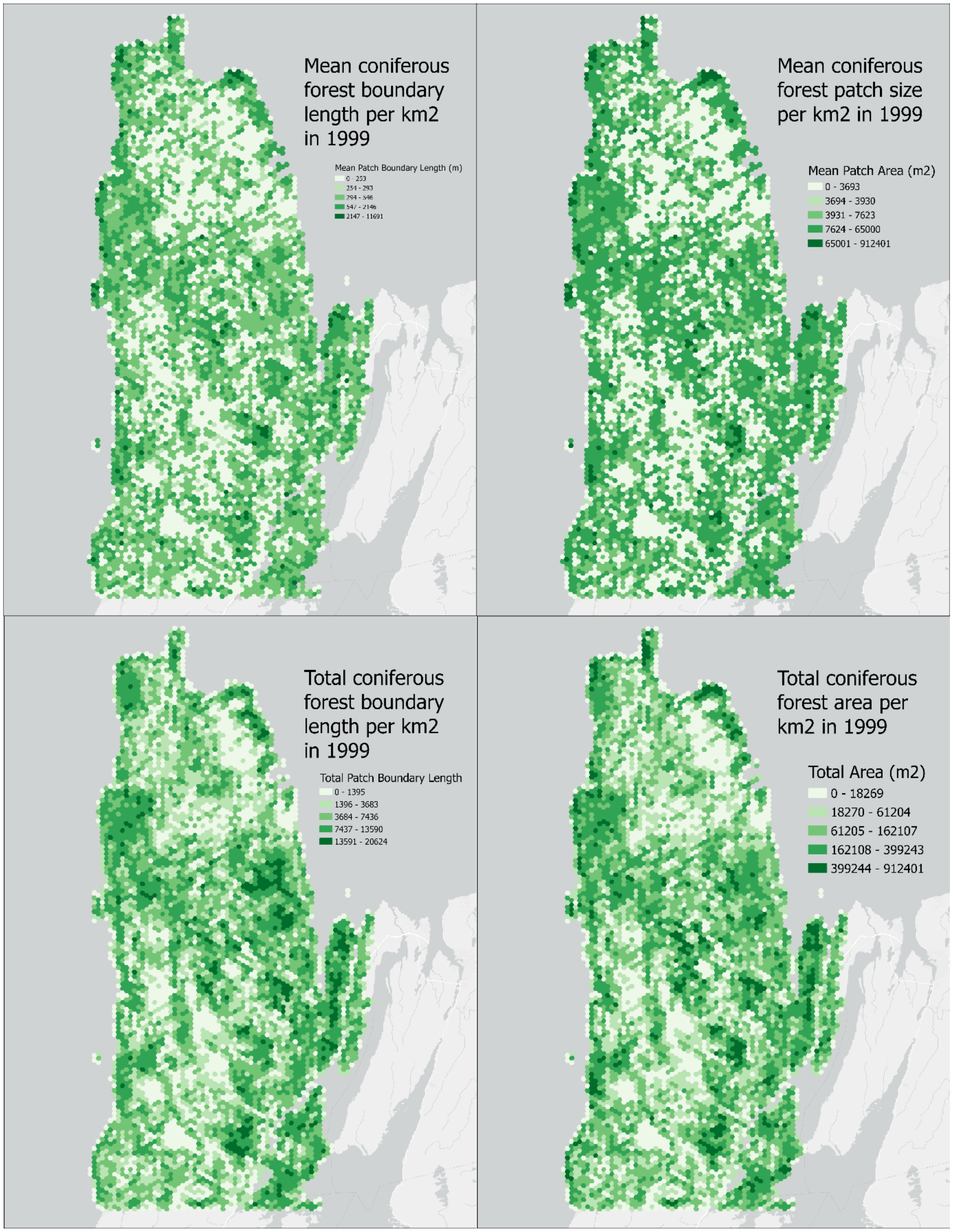

Figure D.3 Analysis of forest cover per km: mean stand boundary length (perimeter) and area; and total stand boundary length (perimeter) and area for 1999.

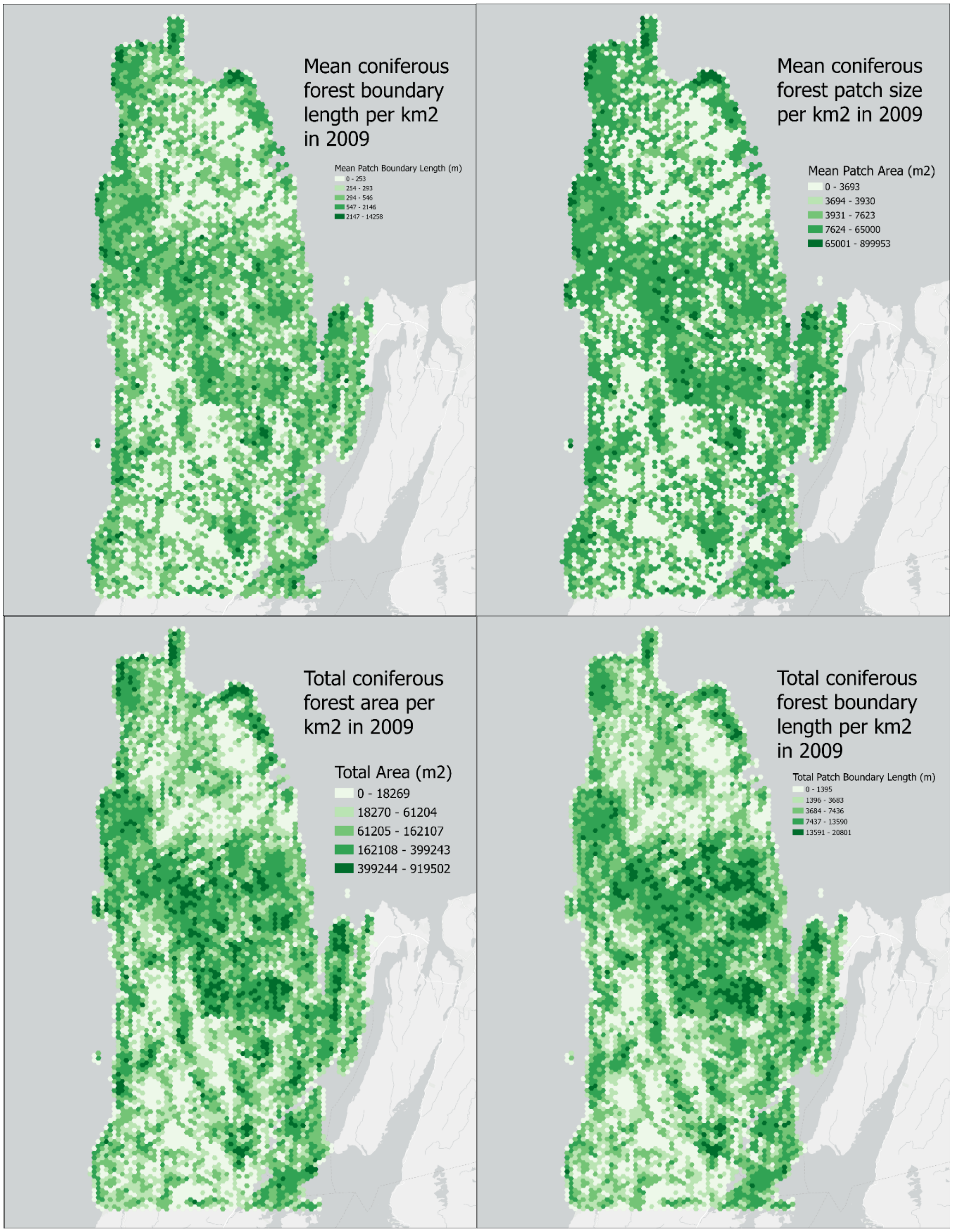

Figure D.4 Analysis of forest cover per km: mean stand boundary length (perimeter) and area; and total stand boundary length (perimeter) and area for 2009.

Figure D.5 Analysis of forest cover per km: mean stand boundary length (perimeter) and area; and total stand boundary length (perimeter) and area for 2019.

APPENDIX F INDIVIDUAL MAPS OF CONIFEROUS FOREST CONNECTIVITY VALUE AT EACH TIME STEP

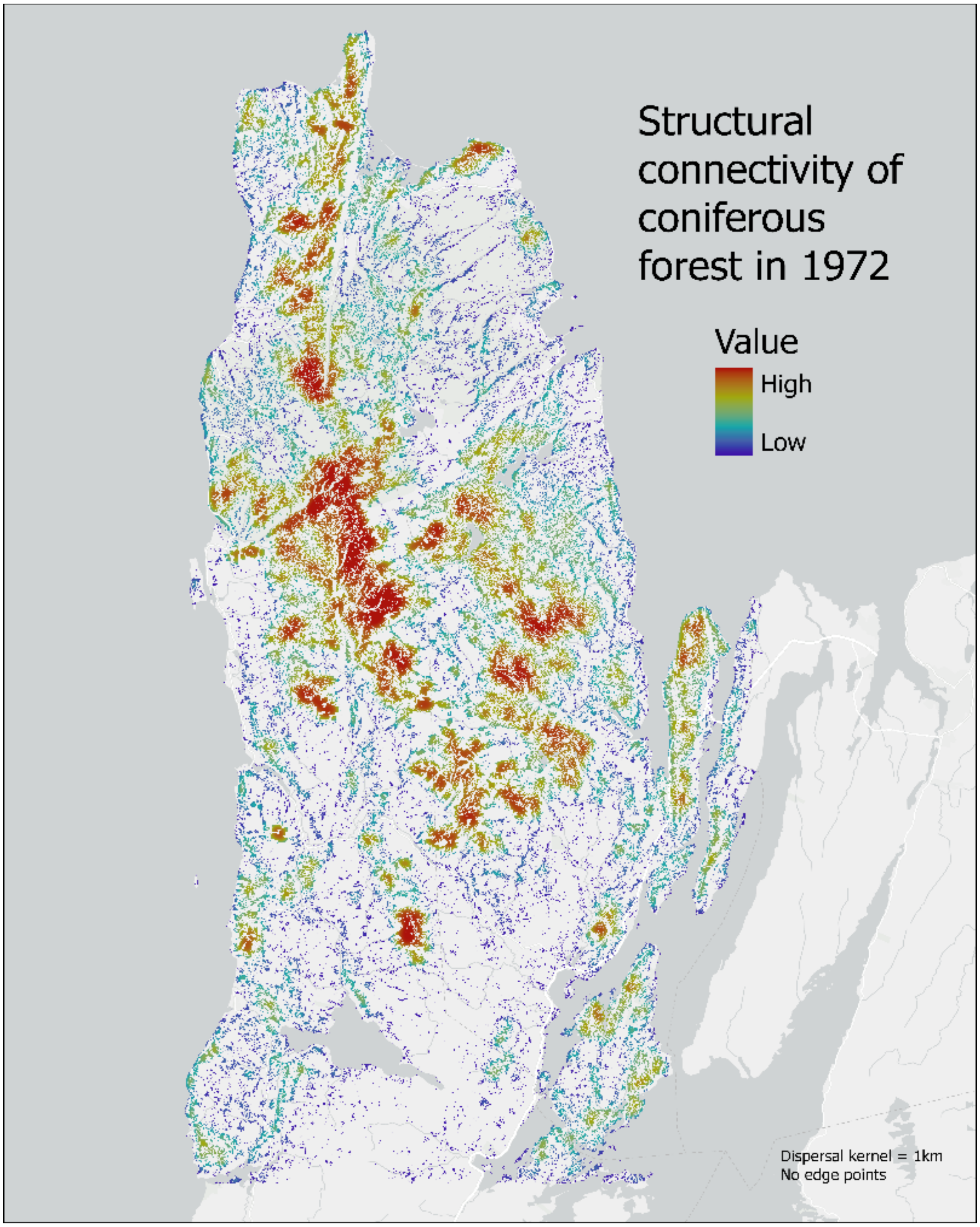

Figure F.1 Structural connectivity of coniferous forest in 1972 using dispersal kernel of 1 km.

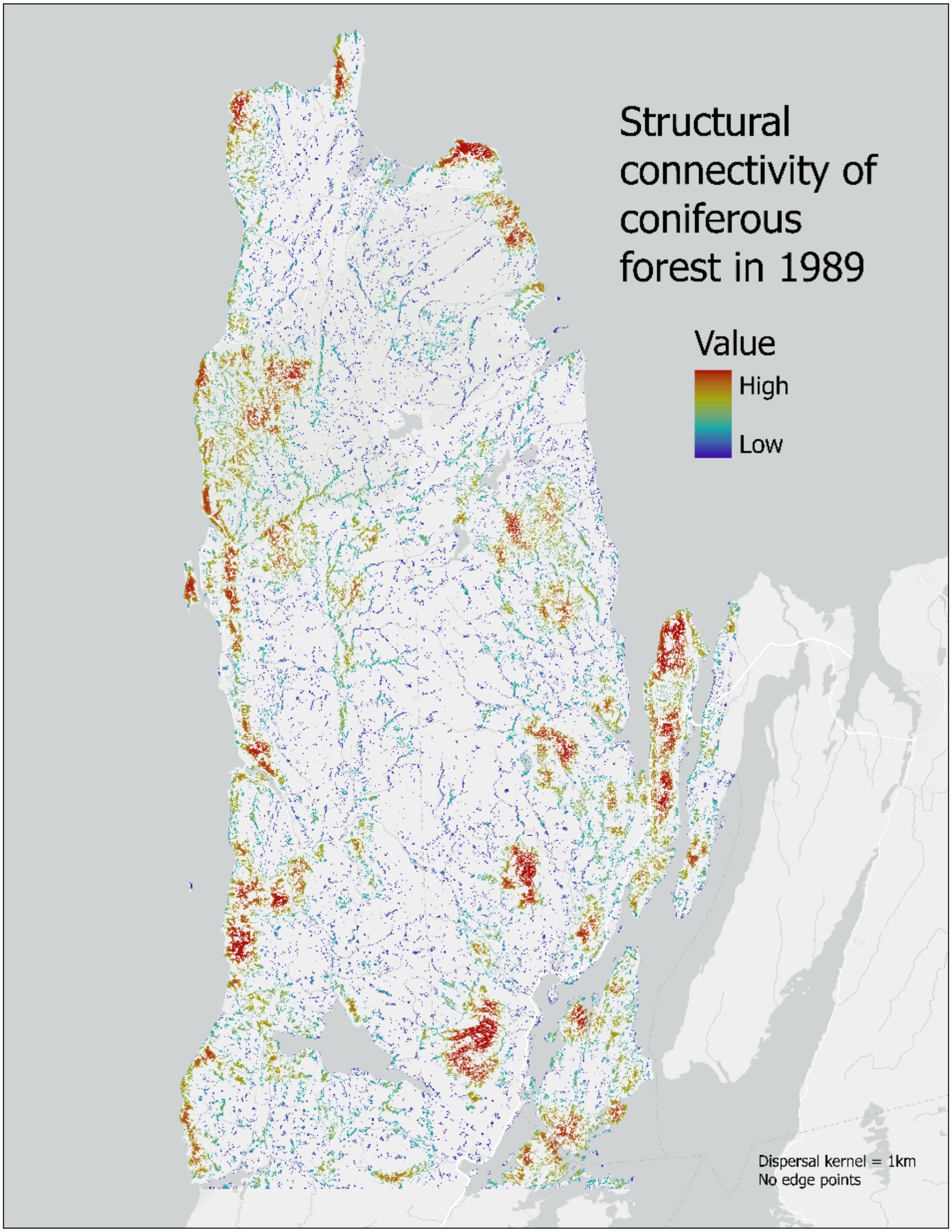

Figure F.2 Structural connectivity of coniferous forest in 1989 using dispersal kernel of 1 km.

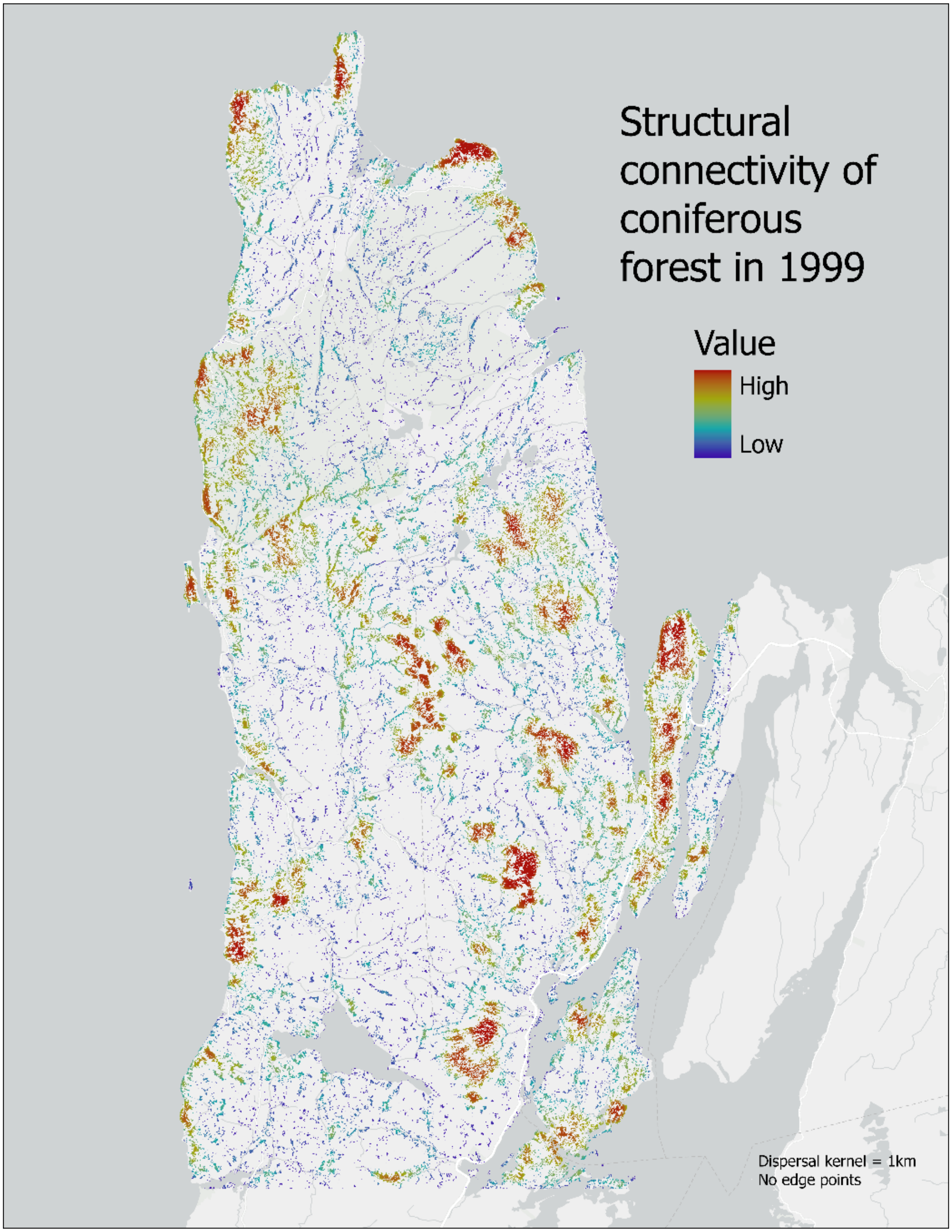

Figure F.3 Structural connectivity of coniferous forest in 1999 using dispersal kernel of 1 km.

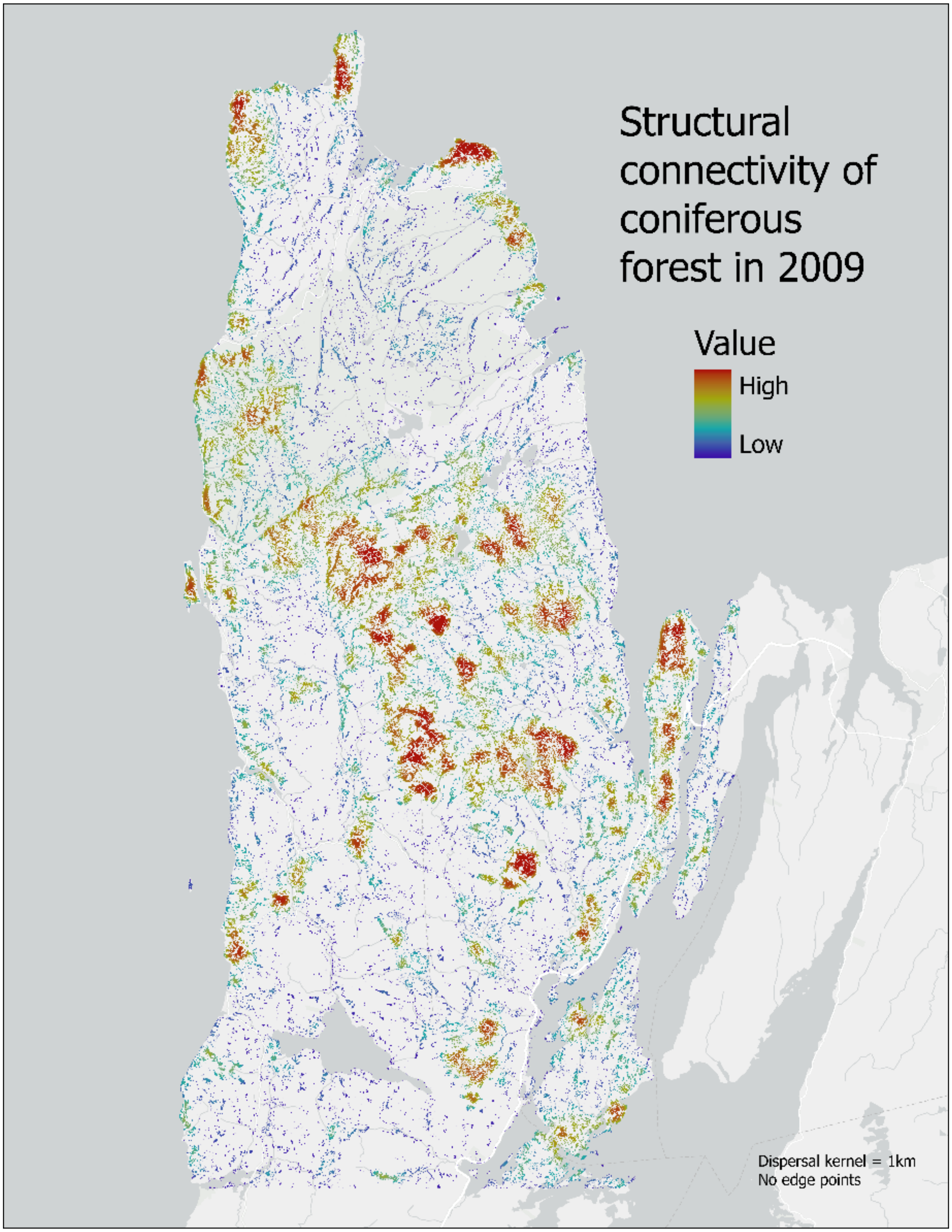

Figure F.4 Structural connectivity of coniferous forest in 2009 using dispersal kernel of 1 km.

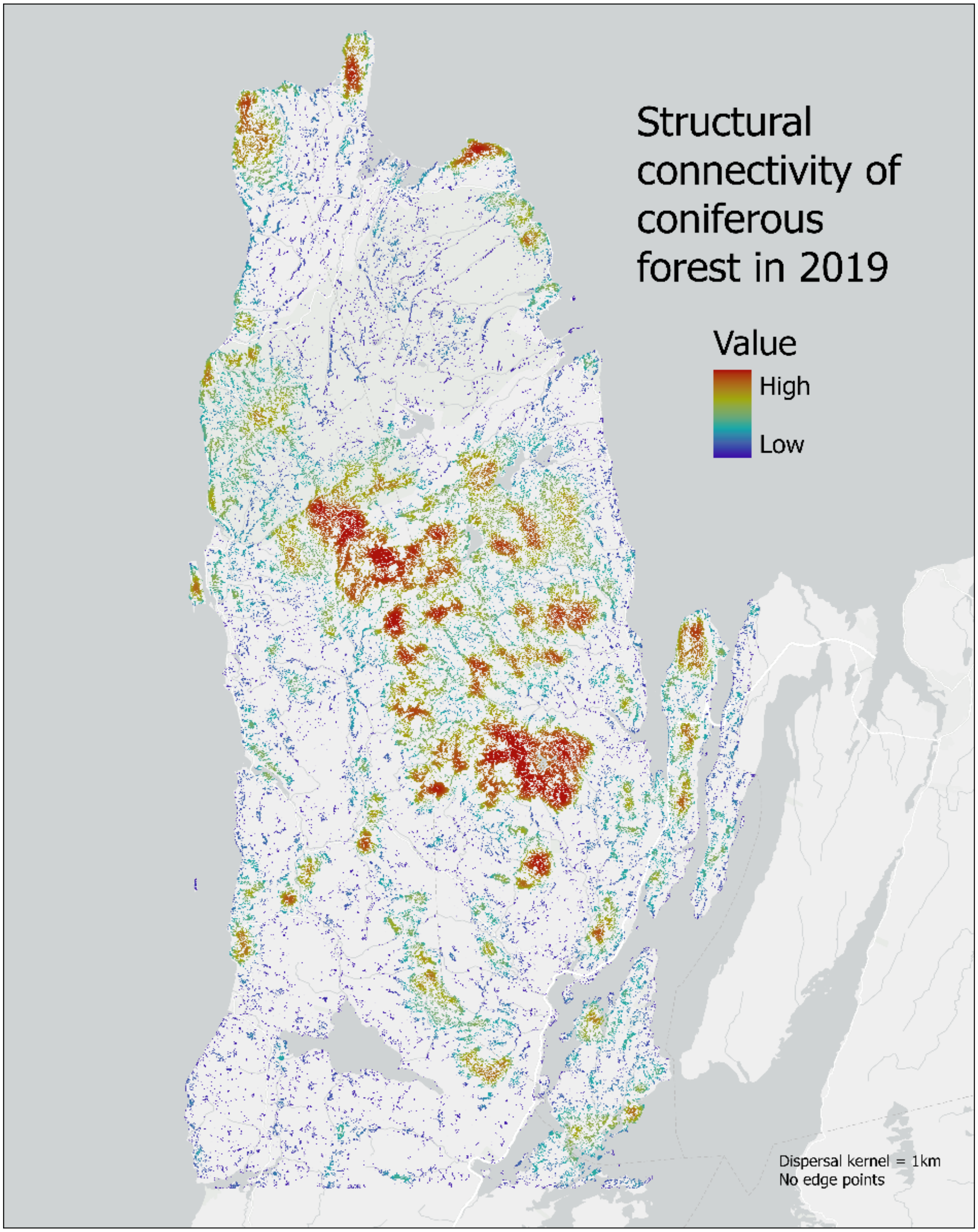

Figure F.2 Structural connectivity of coniferous forest in 2019 using dispersal kernel of 1 km.