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Statistical Methods and Tools for Cross-scale Modelling

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Statistical Methods and Tools for Cross-scale Modelling

SFM Network Project: Large Scale Issues in Sustainable Forestry

By

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ABSTRACT

This project, which is one of several interrelated projects undertaken by the Boreal Ecology and Synthesis Team (BEEST), completed four research components in the past three years. The first component was the development of FEEnix, a spatial simulation tool that can be used to evaluate the ecological and economic consequences of alternative forest management practices at large spatial and temporal scales. FEEnix comprises four main submodels including a harvest scheduler and road builder, a wildfire ignition and spread submodel, a mixedwood stand dynamics submodel, and a set of habitat models predicting the distribution and abundance of forest birds. In the second research component we explored the feasibility of modelling spatially explicit landscape pattern indices from nonspatial stand attribute tables. We sought indices that have been shown, in the literature and with our own habitat modelling initiatives, to be important correlates of bird abundance and community structure. Using only three landscape variables obtained directly from stand attribute tables (total habitat area, and the mean and standard deviation of habitat patch size), our statistical models explained more than 73% of the joint variation in five landscape pattern indices (representing patch shape, forest interior habitat, and patch isolation). In the third research component we used bird survey and forest inventory data, from the boreal mixedwood forest in Alberta, to develop statistical models relating bird abundance to habitat characteristics measured at two spatial scales. Bird abundances were estimated from 1-6 years of point count surveys at over 400 stations. At the local scale (3-ha buffers centered on point-count stations) we measured patch attributes such as canopy height and crown closure. At the neighbourhood scale (74-ha annular buffers), we characterised the forest composition and configuration. Poisson regression models developed for five species using both local and neighbourhood habitat variables explained up to 73% of the variation in abundance. The importance of empirical model validation using independent data is discussed, especially when habitat models will be used to evaluate management scenarios over large spatial and temporal scales. In the fourth research component we began linking FEEnix and our newly developed habitat models to explore interactions between alternative harvesting scenarios, fire regimes and stand dynamics on bird species abundances and community structure. In the final section of the report we provide a brief summary of three Master's theses partially funded by the Sustainable Forest Management Network.

ACKNOWLEDGEMENTS

P. Vernier and S. Cumming were explicitly involved in much of the research presented here. We thank T. Morcos, D. Demarchi, and R. Pelletier for computer and GIS assistance, S. Hannon for her collaboration in the Calling Lake Fragmentation Experiment, and the numerous field assistants who collected the point count data. This research was supported by the Sustainable Forest Management Network and by Alberta Pacific Forest Industries Inc.

INTRODUCTION

A broad goal of the SFM Network is to synthesize information from various research sources into appropriate practices for sustainable management of the boreal forest. At present, there is a general view that harvesting should emulate to some degree the natural disturbance regime, the spatial aspect of which remains incompletely understood. There also is a need for accounting and simulation tools that can evaluate just how well this objective can be achieved at an operational level, and whether it makes sense to do so. Further, it is necessary to quantitatively evaluate the ability of management alternatives to satisfy multiple and evolving ecological and socio-economic objectives. To this end, the Boreal Ecology and Economic Synthesis Team (BEEST) undertook integrative/simulation studies of stand dynamics, pursued collaborative work on fire modelling, developed empirical habitat models, and implemented approaches to using such models in operational-scale planning tools. Thus, the main objective of the BEEST, which includes this project, was to develop an integrated suite of models of natural forest dynamics and forest management, that facilitate the evaluation of management scenarios. Our focus was on the assembly and analysis of existing data sets, and the creation of analytic and modelling frameworks that permit the inclusion of new data as it becomes available. The scientific research areas included stand dynamics, spatial patterns in fire ignition and spread, the effect of fire suppression, and the statistical and simulation modelling of these and other processes, including wildlife habitat.

Our specific objectives for this project were (1) develop and parameterise landscape simulation and planning tools, (2) explore relations between spatial and aspatial forest characteristics, (3) develop a set of empirical models of forest bird distributions, and (4) explore the interactions between forest management, fire and stand dynamics, and the consequences of changes in landscape structure on forest bird communities. Objective 1 was tightly coupled with the companion project of Beck, Adamowicz and Schmiegelow, whilst objective 3 is similarily integrated with Schmiegelow and Beck. Objective 4 is an ongoing initiative that involves many BEEST members. We also briefly report on the successful completion of three Master’s theses.

STUDY AREAS

We used two study areas: one to explore explore relations between spatial and aspatial forest characteristics (objective 2) and the other to develop habitat models (objective 3). Our coarse-scale study area comprises about 7,500,000 ha of boreal mixedwood forest (Rowe 1972), on the southern edge of a large forest estate in northeast Alberta, Canada (approx. 56° N, 113° W; Figure 1). Our fine-scale study area encompassed ≈140 km^2 of boreal mixedwood forest near Calling Lake, in north-central Alberta, Canada (55° N, 113° W; indicated by the star symbol in Figure 1). The mixedwood region is transitional between colder, conifer-dominated forests to the north and warmer, drier aspen parklands to the south (now largely farmland). Mean summer (early June through mid-August) precipitation in the region is ≈320 mm, accounting for >70% of the total yearly precipitation; July is generally the wettest month. The mean summer temperature is 12.0°C, and the mean frost-free period is 85 days (Strong and Leggat 1981). The most abundant tree species are trembling aspen (*Populus tremuloides* Michx.), balsam poplar (*P. balsamifera* L.), black spruce (*Picea mariana* (Mill) B. S. P.), jack pine (*Pinus banskiana* Lamb), and white spruce (*Picea glauca* (Moench) Voss). The dominant understory shrubs are alder species (*Alnus tenufolia, A. crispa*) with lesser amounts of willow (*Salix* spp.). Various fruiting shrubs (*Rubus, Rosa* spp.), sarsaparilla (*Aralia nudicaulis*), and other herbaceous plants dominate the lower strata. Wetland areas are abundant in the mixedwood, and cover about 50% of the shaded region in Figure 1, but only 10% of our actual study landscapes. The region has generally low relief, with limited variation in landforms and topography. Historically, stand-replacing fires and insect outbreaks have been the dominant disturbance agents.

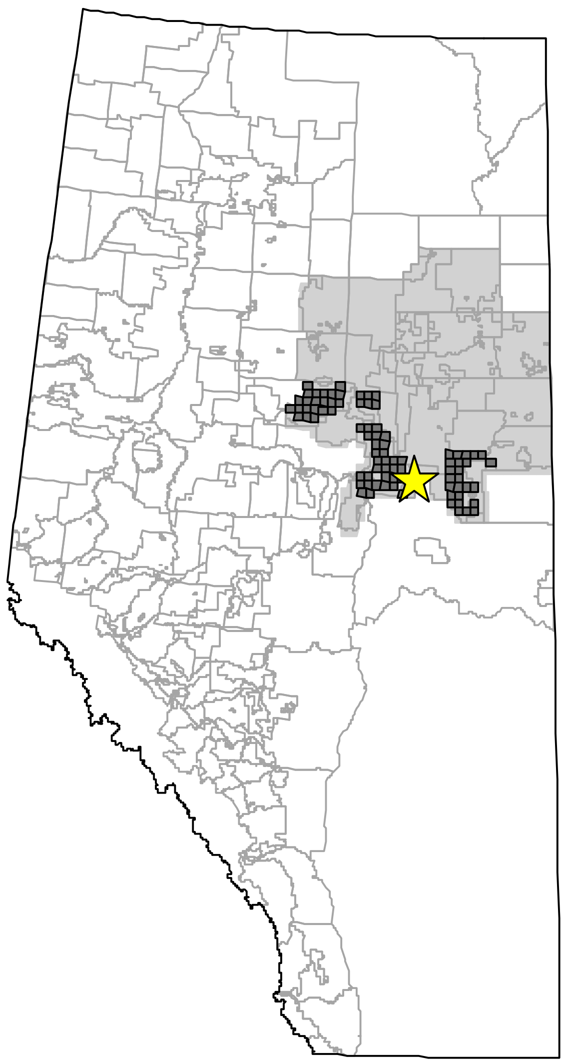


Figure 1. Study area location in northern Alberta with 84 selected townships highlighted in dark grey. The light grey area is the forest estate from which townships were selected. Irregular polygons represent forest

management unit boundaries in Alberta. The location of the Calling Lake study area is indicated by the star.

OBJECTIVE 1: LANDSCAPE SIMULATION MODELLING (FEENIX)

We developed an integrated landscape simulation model for applications to forest management and habitat conservation problems in the boreal mixedwood forest. The regionally-specific model components are fire, mixedwood stand dynamics, hierarchical harvest scheduling, and habitat modelling. These components are continually evolving along with the underlying research programmes and it is expected that design decisions, model components and process parameters will undergo further changes in the future. The current version of the model is known as FEEnix – Forest Ecosystem Emulator.

FEEnix was originally developed from an existing simulation model that was developed to provide an objective and quantitative tool for comparing forest harvesting and conservation policies for the spotted owl and other rare species (Demarchi 1998). The previous version of the model consisted of an individual-based population dynamics model which is linked to a detailed spatial simulation of forest harvesting, to represent as accurately as possible the forest landscape changes that a particular species of wildlife will face. The model has been used to evaluate alternate forest management policies aimed at protecting and conserving the northern spotted owl on timber supply areas in the vicinity of Vancouver, B.C. The most recent version of the model software was written in Visual Basic 6.0 and runs under Microsoft Windows (Figure 2). A summary of the major refinements and new additions to the current version of FEEnix are described below (see also Cummings et al. 1998 for more details).

Characteristics of FEEnix

Spatial resolution and extent. Earlier versions of the model ran at low spatial resolutions. In some applications, harvest scheduling was limited to clearcut logging at a 2500 ha resolution. This was clearly undesirable, and as technology developed, the potential for higher resolution modelling was realised. In the spotted-owl modelling application, a spatial resolution of 25 ha and a spatial extent of $\approx 2.3 \times 10^6$ ha was used. This resolution approaches the extent and grain of actual forest practices. The current version of the model, FEEnix, has been developed at a 9 ha resolution, and will be able to simulate areas as large as several million ha.

Input data layers. FEEnix reads and operates on raster-based ASCII map files, such as those that can be generated from ArcView and GRASS geographic information systems (GIS). The study region and desired spatial resolution must be defined beforehand, as part of the data assembly phase. Once entered, data layers can be manipulated thru the interface, either before or during a simulation run. This feature is especially useful in modelling workshops. In forestry applications, data layers typically include location, forest type and age, site productivity indices, road access and potential hawl routes, forest reserve status, a classified habitat map, and an optional elevation map. Most of the layers can easily be obtained from existing digital forest inventory data such as the Alberta Vegetation Inventory (AVI).

Harvest scheduling and dynamic road building. FEEnix generates timber harvest schedules based on a number of economic and operational criteria. Resultant changes in forest structure can then be used to assess relative responses of other model processes over time via the component submodels of fire, stand dynamics, and wildlife habitat. The most important aspect of the forest harvesting component is that it acts at a resolution and precision comparable to that of the underlying digital forest inventory data (9 ha). Cut-levels and operability, scheduling and blocking rules (how cells are aggregated into larger harvestable units) can be combined to create a rich array of harvesting strategies and local tactics. Haul costs are an important consideration of any logging plan. By finding optimal log hauling routes from each forest cell to the nearest mill, the model can locate and cut the timber based not only on its characteristics, but on whether or not it is economical to harvest. Currently, road access is computed to grid-cell resolution which is unecessarily high for the present application. If the dynamic road-building feature proves useful in the mixedwood context, later versions will reduce the precision of the road construction and access to something more reasonable (e.g., townships).

Wildfire simulation. In this version of FEEnix, only lighting caused fires are considered. The model treats fire as a three stage stochastic process. Stage 1 models the ignition process, and determines if a fire actually starts in a particular grid cell in a given model time step. Stage 2 models the effect of fire suppression, in effect determining a probability that a fire stays within the cell of origin. Stage 3 models fire growth, using spread parameters or "jump probabilities" which determine the probability of a fire spreading across a cell boundary, from a burning cell into an unburnt neighbour. These three processes depend on parameters that can be set by the user, using a dialog box.

Mixedwood dynamics. This component, designed *de novo,* is crucial for correct representation of fire ignition and spread, studying interactions between harvesting and fire, and projecting the future distribution and availability of white spruce. Our objective was to define a biologically reasonable model of the dynamics of mesic stands, using as few parameters as possible, and which implicitly makes use of allometric relationships such as that between volume and seed production. The mixedwood dynamics model consists of 5 submodels: seed production, seed dispersal, substrate, recruitment, and stand dynamics. We have attempted to keep the model dimensionless. Most components (seed production, recruitment, etc.) are described by variables or functions which take values between 0 and 1. We believe that most of the empirical claims and assumptions can be supported by the current literature on white spruce ecology and aspen stand dynamics.

Wildlife-habitat models. The habitat model component, also designed *de novo*, complements the existing individual-based modelling capability of FEEnix. Unlike the latter model component that is restricted to a few species for which detailed demographic data is available, habitat models have been developed for many resident and migratory forest birds that occur in the boreal mixedwood forest. The habitat models were developed using the same approach that is described in the section on "Statistical Habitat Modelling" (see also Schmiegelow et al. final report for additional details). The main difference is that the habitat models built for FEEnix are based on a grid representation of forest inventory data, whereas the models described below are based on the original vector representation. The resultant grid-based habitat models predict the abundance of forest bird species at each pixel in the landscape. The output maps can then be optionally aggregated to display suitability classes based on, for example, low, medium and high abundance values. As with other model components described above, parameter coefficients can be changed by the user through a dialog box. This feature facilitates the application of FEEnix in other geographical regions where parameter estimates may vary.

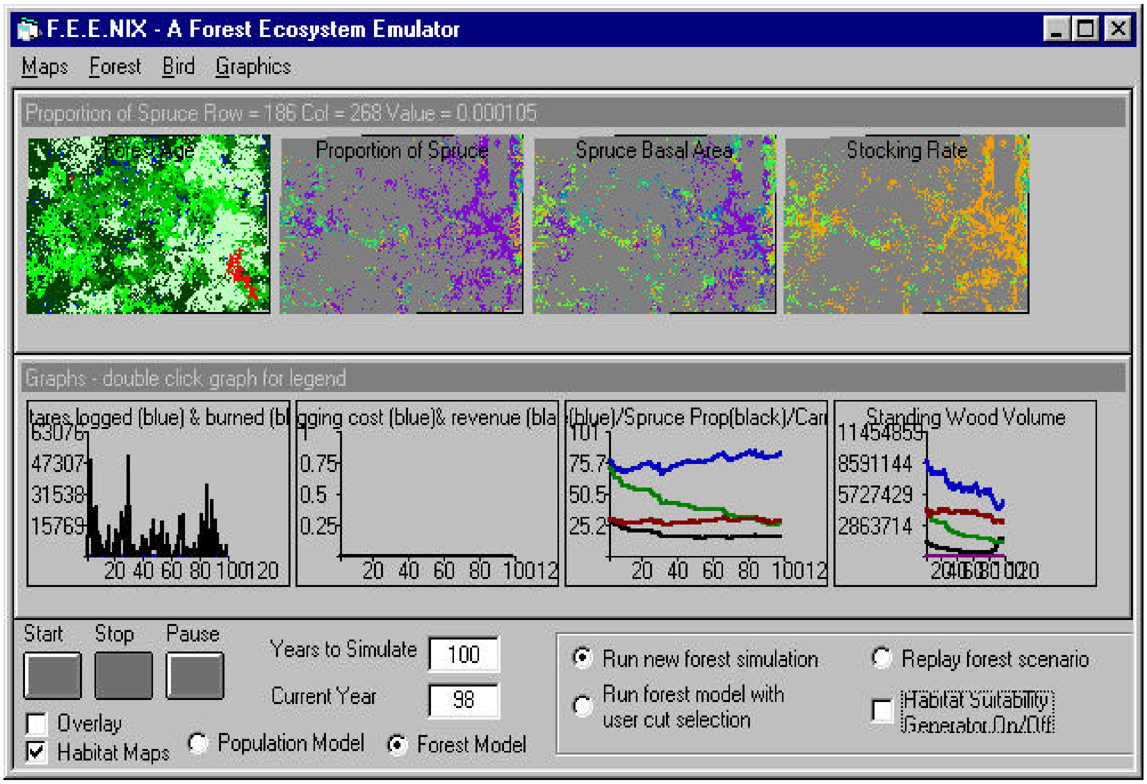


Figure 2. Screen capture of a FEEnix simulation run showing several maps and graphs tracking various economic and ecological indicators.

Other applications

D. Demarchi has worked with several University of Alberta researchers (B. Olsen, J. Hoyt, S. Hannon) to explore application of the individual-based modelling capabilities of FEEnix to two boreal landbird species: the barred owl, and the three-toed woodpecker. The latter case involves some interesting potential interactions between wildfire and dispersal. More recently, Rohner, Demarchi, Walters and Schmiegelow have used FEEnix to model woodland caribou populations in cooperation with the West-Central Alberta Caribou Committee.

Future development

The resolution of a planned future version of the model will be reduced to 3 ha to approximate the scale at which bird point count surveys and habitat models were developed. The extent will remain the same. Changing the resolution of FEEnix will entail the re-parameterisation of several submodels. In addition, we are planning more efficient input/output linkages between

FEEnix and some of the major GIS packages (i.e., ArcView, GRASS) used by forest managers and researchers.

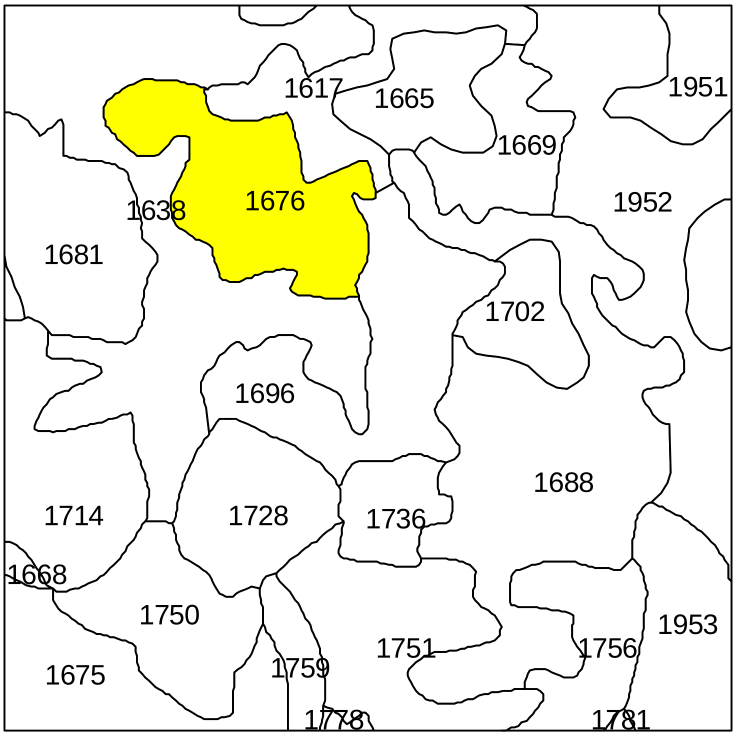
OBJECTIVE 2: CROSS-SCALE MODELLING: PREDICTING LANDSCAPE PATTERN INDICES FROM FOREST STAND ATTRIBUTE TABLES

For some modelling purposes, high-resolution spatially explicit models (e.g., FEEnix) may neither be necessary nor efficient for prediction. For example, members of the BEEST have developed a low-resolution spatial dynamic model that incorporates simulations of forest harvesting decisions (Cumming and Armstrong 1999), and statistical models of wildfire (e.g. Cumming in press) and stand dynamics. Model cells represent roughly 100 km^2 regions (e.g., townships) and cover an area of several million ha simulated over 200 years. Each cell contains aggregated information on hundreds of individual patches whose attributes include size, vegetation structure, age, and disturbance history. There is no representation of patch geometry or configuration within cells. Nonetheless, the aggregated data retain enough structure that spatially implicit modelling of ecological processes operating at spatial scales finer than the model resolution is possible, in some cases. A need for appropriately scaled sub-models of wildlife distribution and abundance that could be linked to this particular coarse-scale modelling initiative motivated this component of our project.

Our approach to the problem was to determine if was possible to model spatially explicit landscape pattern indices from nonspatial stand attribute tables. We sought indices that have been shown, in the literature and with our own habitat modelling initiatives, to be important correlates of bird abundance and community structure. Our goal was to develop low resolution models using readily available forest inventory data that consisted of georeferenced stand polygon boundaries and associated stand attribute tables. We refer to summary statistics that can be readily calculated from attribute tables (without requiring information on patch geometry) as stand table indices (STIs). Conversely, we refer to landscape statistics that can only be calculated efficiently using information on patch geometry (e.g., patch shape and interpatch distance) as landscape pattern indices (LPIs.) Our specific objectives were (1) to identify representative and interpretable subsets of LPIs and STIs from the large set of readily computable candidate landscape metrics and (2) to explore the nature and strength of the statistical relationships between these two types of metrics (Figure 3). We used townships (≈9500 ha) as our sample landscapes.

Methods and results

The complete methodology, from data assembly to statistical modelling, is illustrated in Figure 4. The main steps are briefly described below and more details can be found in Vernier and Cumming (1998). We first selected 84 township-size digital Alberta Vegetation Inventory (AVI) maps that were available for portions of our project's broader study area (Figure 1). Only maps having little or no missing data and where the landscape matrix was mostly forested were used. Using AVI stand-attribute data, we developed a habitat classification system based on the dominant canopy tree species (or genus in the case of *Populus*), estimated stand age, and management history. We used ArcView (Esri 1998) to grid each map to a resolution of 1 ha using the derived habitat class attribute, and then used FRAGSTATS (McGarigal and Marks 1993) to compute a suite of LPIs from these classified raster maps for 4 of the 9 habitat classes: young deciduous, old deciduous, white spruce, and mixedwood forests. These 4 classes comprise the most commercially valuable portion of the mixedwood forest, and have attracted the most research effort directed at quantifying avian habitat associations. They are thus of particular interest for cross-scale habitat modelling.



Stand_id	Stand_area	Stand_ht	Stand_age	Hab_class
1669	17525	28	125	4
1675	549481	11	95	6
1676	37928	27	115	8
1681	35123	23	105	5
1688	83579	30	135	5
…	…	…	…	…

Figure 3. Example of forest inventory data with a stand boundary map (top) and an associated stand attribute table (bottom). The former was gridded and used to compute landscape pattern indices (LPIs) while the latter was used to calculate stand table indices (STIs).

For each of the four focal classes in each of the 84 maps, we computed 29 class-level LPIs (all the class-level metrics that FRAGSTATS supports), including a variety of edge, patch-shape and core-area metrics, nearest-neighbor metrics, and contagion and interspersion metrics. These metrics constituted our initial candidate set of LPI variables (dependent variables). For our candidate independent variables, we computed 8 STIs for each of the habitat classes, directly from AVI stand attribute tables exported from ArcView. Because many of both the STI and LPI variables are strongly correlated, we performed a variable reduction procedure following the approach described by Ritters *et al.* (1995). This included a pairwise correlation analysis followed by a principal components analysis. For the statistical modelling phase we retained variables with high component loadings (> 0.80) and which were not highly correlated with each other (r > 0.9).

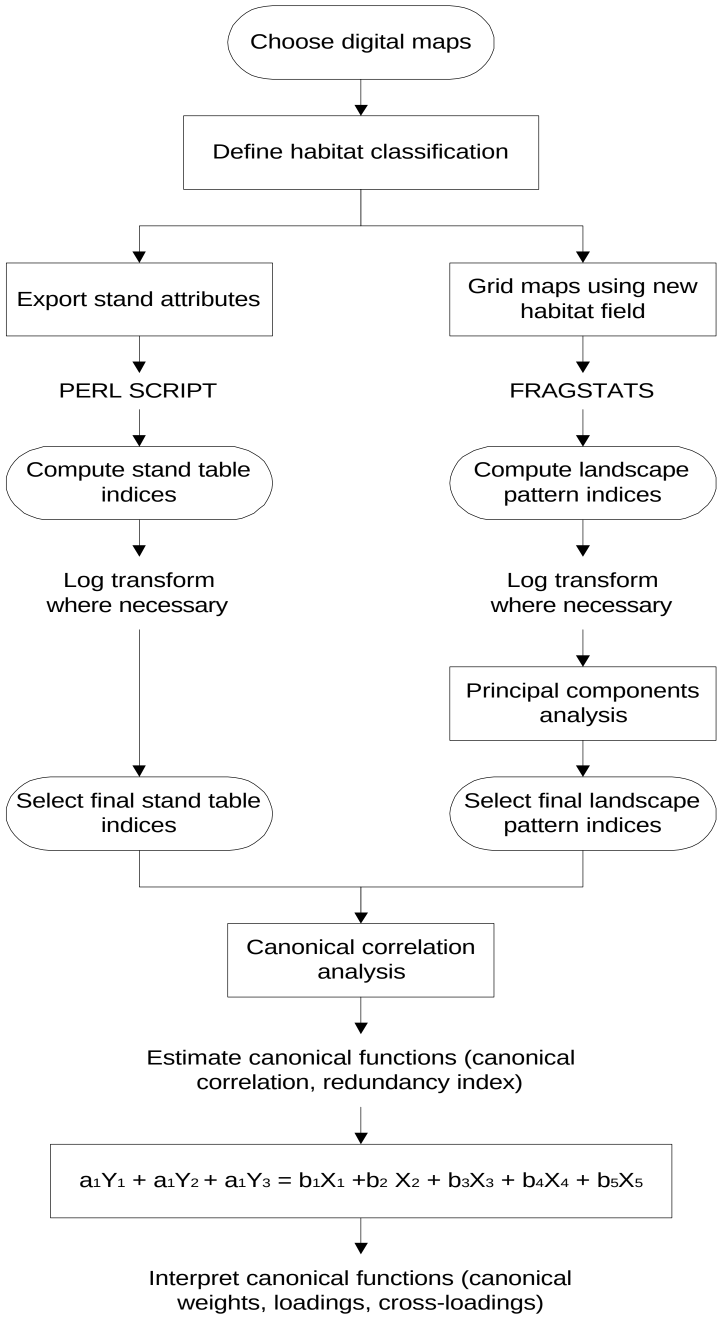


Figure 4. Procedure used to develop the statistical relationships between STI and LPI variables (see text).

To model the relationship between the STIs and LPIs, we performed a Canonical Correlation Analysis (CANCOR) – a generalization of multiple regression, where multiple dependent variables are simultaneously related to multiple independent variables. For each habitat class, we performed the following steps:

1) The three STIs surviving the variable reduction step were selected as the set of independent variables.

2) From each principal component retained during the PCA step, we chose the component variables with high loadings as the set of dependent variables for the class.
3) We then performed a CANCOR on these sets of variables, unless only one LPI loaded highly on a given principal component, in which case we performed a multiple regression analysis.
4) We assessed the resultant multivariate models by considering the magnitude of the canonical correlation coefficients, its significance level, and the redundancy indices for each variate.

Our results indicate that using only three landscape variables obtained directly from stand attribute tables (STIs measuring total habitat area, and the mean and standard deviation of habitat patch size), our statistical models explained more than 73% of the joint variation in five landscape pattern indices (LPIs representing patch shape, forest interior habitat, and patch isolation). Moreover, predictor variables and strengths of association were highly consistent across habitat classes (Vernier and Cumming 1998).

Application of CANCOR models

To illustrate the intended application of this research, we used a multiple regression model based on the CANCOR analysis to simulate the spatial dynamics of one LPI in a large managed landscape subject to disturbance by wildfire. Specifically, we modeled log(MPI) – mean proximity index, a measure of the degree of isolation and fragmentation of a patch type – for old deciduous (class O_DECID) for 825 townships on a roughly 74,000 km sq forest estate in the boreal mixedwood (shown in Figure 1), using a prototype of the low-resolution landscape simulator mentioned in the introduction. We ran the model for 100 years of simulated harvesting and wildfire. The model was initialized from stand-attribute tables (described above); the harvest scheduler and table-driven stand dynamics component are described by Cumming and Armstrong (1998); the wildfire component is based on township resolution models of fire composition (Cumming, in press), fire size (Cumming 1999) and ignition (Cumming, unpublished data). The annual rate of harvest in the commercially valuable forest (essentially the four focal habitat classes) was approximately 1%. The mean annual rate of burn was approximately 0.3%, consistent with the recent historical record (1940-1995) reconstructed by Cumming (1997). After 100 years of simulated harvesting and fire, the distribution and township-scale pattern of old deciduous stands has changed markedly (Figure 5). The two patterns are uncorrelated according to Pearson (r=0.10,p=0.074) and Spearman (r=-0.099,p=0.084) coefficients.

Discussion

Our STIs are easily calculated from stand attribute tables contained in forest inventories that cover the boreal mixedwood. Similar data are available throughout the boreal forest of Canada (Gillis and Leckie 1993). The spatial scale of our analysis (the size of our sample landscapes) is consistent with the spatial resolution of these inventories. Only the habitat classification system would need to be modified to repeat our analyses in different parts of the boreal forest. The strong canonical correlations obtained in this analysis have important implications for habitat modelling in the boreal mixedwood forest. These relations show that stand attribute tables may be used to characterize not only patch sizes and proportional amounts of habitat types, but also several aspects of their spatial structure and distribution within a landscape (*i.e.*, patch shape, core area, and patch isolation). Thus, it is possible to incorporate both the amount and configuration of different habitat types within large-scale simulation models, without explicitly representing the underlying landscape. This will greatly simplify some of the technical aspects of model development and data acquisition, and greatly speed model execution time. Also, spatial factors can be incorporated into models developed for areas where digital maps are unavailable.

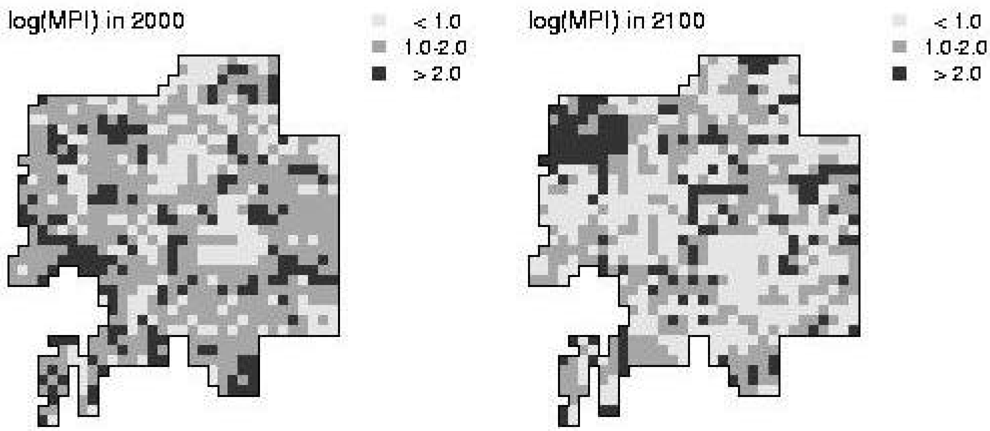


Figure 5. Predicted values of logMPI for class O_DECID, at present, and after 100 years of simulated harvesting and fire. The mapped areas contain over 800 townships; the region is shown in outline in Figure 1. Over 100 years, a substantial rearrangement of this component of the forest is apparent.

Three of our habitat types are harvested (excluding young deciduous forests). Industrial forestry is likely to reduce their amounts below any of the theoretical thresholds predicted to be important for area sensitive species. The configuration of the remainder will therefore become an important management issue. Current forest practices will fragment the non-harvested residual areas of these types almost as much as is possible. They will be left as long linear features associated with stream buffers, or as small inoperable patches, surrounded, e.g. by wetlands. This outcome could in principle be altered, so that for example, residual areas of these types were concentrated in a few large patches within each township (e.g., Bunnell et al. 1999) . This change in practice would not necessarily alter the total residual area. Thus, evaluation of alternate management practices may well require the ability to model changes in habitat configuration as such, independent of abundance. We have indicated, using a prototype low-resolution landscape model, how this can be done over large areas, by exploiting the statistical relations we developed between stand table and landscape pattern indices.

OBJECTIVE 3: STATISTICAL HABITAT MODELLING

Effective wildlife conservation in managed forest landscapes increasingly relies on wildlife habitat relationships models to predict the outcome of alternative management scenarios on the distribution and abundance of focal species. Habitat models based on remotely sensed data such as forest inventories or satellite imagery are inexpensive to develop compared to models based on detailed vegetation data collected in the field, and may be as effective in predicting abundance at the spatial scales considered here (Schmiegelow, Vernier and Cumming, unpublished analysis). As our goal is prediction at scales commensurate with forest management planning, candidate independent variables should be derivable from available spatial data. We have developed such a set of statistical (empirical) habitat models using bird survey and forest inventory data from the mixedwood region of the boreal forest in Alberta. Using a generalized linear modelling approach, we developed poisson regression models which predict the abundance of forest bird species given information about local habitat characteristics and surrounding (neighbouring) forest patterns. We have started to use the habitat models presented here within FEEnix to evaluate the consequences of alternative management activities and policies over spatial extents of several thousand square km and time horizons of at least 100 years (e.g., Schmiegelow et al. unpublished analysis). In this section we describe the model development process. A summary of the habitat models are provided in Schmiegelow et al. A more detailed description of the methodology, results, and discussions can be found in Vernier et al. (2001).

Bird survey data

We used bird abundance data collected by point-count surveys conducted between 1993-98 as part of the Calling Lake Fragmentation Experiment and related studies (e.g., Schmiegelow et al. 1997). A total of 406 permanent sampling stations were located within 65 sites, which we define as contiguous areas of similar forest type and age (Figure 6). Site types included areas clearcut in 1993 as part of the experimental design, young and old deciduous forests, mature coniferous forests, and mixedwood forests. There was a least 200 m between each sampling station. In every year that a station was sampled, point counts were conducted five times during the breeding season, at 10-day intervals, from the third week in May through early July. Sampling effort, in years, ranged from from one to six years across stations, as resources allowed additional survey points to be added to the main experimental design described by Schmiegelow et al. (1997). We developed models for over 20 bird species representing a range of observed abundances and expected responses to forest fragmentation (Schmiegelow and Hannon 1999). For each bird species, we calculated the mean abundance per station per year (after Schmiegelow et al. 1997), and multiplied (weighted) this by the number of years a station was sampled (between 1 and 6 years). We used this aggregated count value as our response variable in subsequent statistical modelling (see Schmiegelow et al. 1997 and Vernier et al. 2001 for details).

AVI-based habitat data

We used AVI data to measure habitat characteristics at two spatial scales which we refer to as the "local" and "neighborhood" scales. At the local scale, commensurate with the territory sizes of species considered here (Schmiegelow, unpublished data), and with the resolution at which bird observations were recorded, we measured forest characteristics such as stand height and crown closure in a 100-m radius buffer. At the neighbourhood scale we placed a 400-m wide buffer surrounding the local habitat patch, where we measured the abundance and configuration of different forest cover types and anthropogenic features. The neighbourhood size was selected, in part, to be consistent with the scale at which other ecological phenomena, such as fire ignition and spread, are represented in FEEnix. We consider both of our scales to be consistent with a broad interpretation of Johnson's (1980) second-order habitat selection, in which habitat composition and configuration are characterised at multiple scales, at the level of territories.

Figure 6. Distribution of forest habitat (light grey), clearcuts (white), lakes (dark grey), nonforest habitats (medium grey), and bird sampling stations in the Calling Lake Study Area.

The forest cover layer of the AVI data contains several attributes useful for modelling wildlife habitat relationships such as species composition, crown closure, height, estimated stand age, and the location of non-forest cover types such as permanent clearings, lakes, and wetlands. Two additional map layers described the location of streams, logging roads, and seismic cutlines. We developed a habitat classification system based on the overstory and understory tree species (or genus in the case of *Populus*), stand age, and management history (Table 1). The classification system was used to create a generalized map of forest and non-forest habitat classes within the study area. The point count stations were georeferenced and linked to the AVI spatial database.

Table 1. Habitat classification system used to calculate several local and neighborhood-level habitat variables.

Class	Description
WATER	Water (lake, ice, river)
NONFOR	Non-forest and wetland
Y_DECID	> 70% deciduous and <= 90 years
O_DECID	> 70% deciduous and > 90 years
W_SPRUCE	> 70% white spruce
B_SPRUCE	Leading black spruce
PINE	Leading pine
MIXED	Mixed deciduous/white spruce
CCUT	Clearcuts < 15 years.
ANTHRO	Anthropogenic (wellsites, large cutlines, etc.)

We used the original and derived map layers to measure habitat characteristics around each bird sampling station at two spatial scales: the local-scale, which matched the size and shape of the circular bird sampling stations (inner buffer of 100 m radius, or 3.14 ha), and the neighborhood scale, which extended from 100-500 m beyond the sampling stations (outer buffer, 75.4 ha). The habitat characteristics we chose have either previously been used in the literature or were hypothesized correlates of species abundance based on the ecology of the species.

Seven variables characterized the structure and composition of the inner buffers (Table 2). A categorical variable (having discrete, unordered values) specified the habitat class at the origin of the station. Four continuous variables quantified the size of the habitat patch containing the origin, and the area weighted means of canopy height, crown closure and proportion of deciduous species in the canopy, for forested habitats intersecting the buffer. Two index variables coded the presence/absence of streams and anthropogenic edges within the buffer.

For each bird species, we selected explanatory variables from the candidate set by a backwards stepwise procedure (P-to-enter < 0.001, P-to-remove <0.0015). A conservative level of significance was chosen as a correction for mulitple tests. Significance levels were based on standard likelihood ratio tests. Model strength was measured using the percent of deviance explained, a measure analogous to the multiple coefficient of determination (R^2).

To evaluate the relative influence of local and neighborhood habitat variables on each species, we compared five alternative habitat models. At the ends of the spectrum were the null and full model. The null model was simply the mean count over all stations while the full model included all local and neighborhood variables. The three intermediate models used subsets of the variables selected by the backwards stepwise procedure: local variables only, neighborhood variables only, or both sets of variables. We used Aikaike's Information Criteria (AIC; Akaike 1974) to select the best of the five models. AIC measures the tradeoff between model goodness-of-fit (measured as the log-likelihood) and model parsimony measured by the number of parameters included in the model. Table 3 shows an example of our model selection approach.

Table 2. AVI-based habitat variables. Local habitat variables were measured within a 100 m radius while neighborhood variables were measured in a 400 m radius beyond each local (inner) buffer.

Variable	Variable type	Range of values	Description
Local			
L_CCUT, L_MIXED, L_ODEC, L_PINE, L_SB, L_SW, L_YDEC	Dummy coded	7 classes	Habitat types in which stations were located (see Table 2 for descriptions).
L_SIZE	Numeric	0.5 – 703.4 ha	Patch size; relies on a habitat classification system (Table 2).
L_DIST	Numeric	0 – 1238.9 m	Distance of station centre to nearest anthropogenic edge (habitat classes 9 and 10).
L_CROWN	Numeric	0 – 85.5 %	Mean crown closure among forested polygons.
L_DEC	Numeric	0 – 1.0	Mean deciduous proportion of forested polygons.
L_HT	Numeric	0 – 31.0 m	Mean stand height of forested polygons.
L_STREAM	Binary	0 or 1	Presence of streams or lakes.
Neighborhood			
N_CUT	Numeric	0 – 0.66	Proportion of neighborhood in a clearcut.
N_MID	Numeric	0 – 0.99	Proportion of neighborhood in mid seral forest (15-90 years).
N_LATE	Numeric	0 – 1.00	Proportion of neighborhood in late seral forest (>90 years)
N_DEC	Numeric	0 – 1.00	Proportion of neighborhood in deciduous forest.
N_MIXED	Numeric	0 – 0.77	Proportion of neighborhood in mixedwood forest.
N_SB	Binary	0 or 1	Presence of black spruce forest.
N_SW	Binary	0 or 1	Presence of white spruce forest.
N_ANTHRO	Binary	0 or 1	Presence of anthropogenic features (well sites, clearings, gravel pits, highways, etc.).
N_WATER	Binary	0 or1	Presence of lakes, ponds, etc.
N_SIMP	Numeric	0 – 0.83	Habitat patch diversity measured usingSimpson's index.
N_EDGEA	Numeric	0 – 319.2 m/ha	Anthropogenic edge density calculated using habitat classification system (Table 2) and edge contrast matrix (Table 4).
N_EDGEN	Numeric	0 – 85.3 m/ha	Natural edge density calculated using habitat classification system (Table 2) and edge contrast matrix (Table 4).

Prior to model development, we assessed the distributional assumptions of our candidate predictor variables, checked for highly correlated pairs of predictor variables, and looked for nonlinear relationships between bird abundances and our continous variables using scatterplots with lowess smoothers. After model development we assessed model assumptions by examining diagnostic plots and maps of the response variables and the model residuals to identify skewness and outliers, assessed the overall behaviour of the model, identified potentially influential observations, and examined the assumption that counts were independent between stations (i.e. no spatial autocorrelation). Finally, we assessed model uncertainty using a *leave-one-out* cross-validation approach. A detailed discussion of our model assessment strategy and our approach to overcome certain problems such as spatial autocorrelation in the count data is provided in Vernier et al. (2001).

Table 3. Summary of alternative habitat models for the Black-throated Green Warbler (*Dendroica virens*). Deviance, percent deviance explained, and AIC are explained in the text. The model with the lowest AIC is italicized.

Model	Habitat variables	Df	Deviance	%Dev Explained	AIC
Null		405	582.7		
Local	L_MIXED, L_ODEC, L_HT	402	333.5	42.8	812.6
Neighborhood	N_LATE, N_DEC, N_SIMP	402	364.7	37.4	843.8
Local + neighborhood	*L_HT, N_CUT, N_LATE, N_DEC, N_SW, N_SIMP*	*399*	*266.4*	*54.3*	*751.5*
Full	All local + neighborhood variables	380	252.5	56.7	775.6

Applications and model validation

In Alberta, forest management planning is largely based on forest inventory information, but the ability of such information to predict species abundances has not previously been evaluated. We attempted such an evaluation, using Poisson regression analysis to model the relationship between bird species abundances observed in the field and habitat characteristics derived from forest inventory data. Poisson regression deals explicitly with characteristics of count data, and is generally more efficient and consistent, and less biased than linear regression models of the same data. Our final models demonstrated good predictive ability with no evidence of bias. We conclude that the approach to modelling abundance presented here is robust and their use in landscape simulations is justified, pending their validation against independent data sets. An important objective for developing AVI-based habitat models is to assess the potential ecological outcomes of various forest management scenarios in the boreal mixedwood forests at a resolution and extent commensurate with management planning. Our fourth objective was to begin evaluating scenarios.

OBJECTIVE 4: SCENARIO EVALUATION

We completed integration of our statistical habitat models (objectives 2 and 3) into FEEnix (objective 1). This integrated approach allows us to explore the effects of alternative management scenarios on forest bird communities over large spatial and temporal scales. Some preliminary simulations have been run (Schmiegelow et al. unpublished analysis) and more are planned for the near future. Specifically we are planning to evaluate the interactions between harvesting strategies (e.g., a two-pass system, a dispersed system, no harvesting), wildfire, fire suppression, stand dynamics, and forest bird abundance and community structure.

GRADUATE STUDENTS

Three Master's students were partially funded by the SFM Network and have all successfully completed their studies.

Donald Demarchi (supervised by C. Walters) defended his thesis: "A Spatial Simulation Model for Evaluating the Response of Rare and Endangered Species to Conservation Strategies and Forest Policies: A Case Study on the Northern Spotted Owl" in April 1998. Don adapted a modelling framework originally developed by C. Walters to compare a variety of policy options for future forest management aimed at protecting and conserving the spotted owl. This same modelling framework formed the basis for the development of FEEnix.

Nyree Sharp (supervised by F. Bunnell) defended her thesis: "Bird-Habitat Associations and Simulated Effects of Logging on Bird Habitat in the Aspen Boreal Mixedwood" in September 1998. Using data provided by the Alberta Environmental Centre (now the Alberta Research Council), Nyree developed a methodology for projecting vertebrate responses to forest practices in the boreal mixedwood. Specifically, she (1) developed relationships between bird abundance and forest habitat attributes and (2) assessed the probable effects of logging on bird abundance.

Kim Lisgo (supervised by F. Bunnell) defended her thesis: "Ecology of the Short-tailed Weasel (*Mustela erminea*) in the Mixedwood Boreal Forest of Alberta" in May 1999. Kim's research was conducted within the forest management area of Alberta Pacific Forest Industries, Inc. (ALPAC). The objectives of her project were to: 1) describe the diet of the short-tailed weasel and differences in the diets of males and females; 2) describe the use of habitats by male and female weasels; 3) describe the structures used by weasels for resting; 4) examine the use of slash by female weasels in 3-year old cutblocks, containing naturally regenerating aspen (*Populus tremuloides*); and 5) propose recommendations for managing habitat of weasels in mixedwood boreal forests.

REFERENCES

Akaike, H. 1974. A new look at statistical model identification. *IEEE Transactions on Automatic Control* AU-19, 716-722.

Bunnell, F.L., R. W. Wells, F.L., Nelson, J.D., and Kremsater, L.L. 1999. Patch size, vertebrates, and effects of harvest policy in southeastern British Columba. Pp. 271-93 *In* J. A. Rochelle, L. A. Lehmann and J. Wisniewski (eds.). Forest fragmentation: wildlife and management implications. Brill, Leiden, Netherlands .

Cumming, S.G., D. A. Demarchi, and C. Walters. 1998. A grid-based spatial model of forest dynamics applied to the boreal mixedwood region. Sustainable Forest Management Network Working Paper 1998-8**.**

Demarchi, D.A. 1998. A spatial simulation model for evaluating the response of rare and endangered species to conservation strategies and forest practices. Master’s thesis, The University of British Columbia.

ESRI 1998. ArcView GIS Version 3.1. Environmental Systems Research Institute, Inc. Redlands, California, USA.

Gillis, M.D., and D.G. Leckie. 1993. Forest inventory mapping procedures across Canada. Information Report PI-X-114, Petawawa National Forestry Institute, Forestry Canada.

Johnson, D.H. 1980. The comparison of usage and availability measurements for evaluating resource preference. *Ecology* 61: 65-71.

McCullagh, D.W. Jr., and J.A. Nelder. 1989. *Generalized Linear Models*, 2nd edition. London: Chapman and Hall.

McGarigal K., and B.J. Marks. 1993. *FRAGSTATS: spatial pattern analysis program for quantifying landscape structure*. Unpubl. software, Dept.Forest Science, Oregon State University.

Riitters, K.H., R.V. O’Neill, C.T. Hunsaker, J.D. Wickam, D.H. Yankee, S.P. Timmins, K.B. Jones, and B.L. Jackson. 1995. A factor analysis of landscape pattern and structure metrics. Landscape Ecology 10: 23-39.

Rowe, J.S. 1972. Forest regions of Canada. Publication No. 1300, Canadian Forest Service, Ottawa, Ontario.

Schmiegelow, F.K.A., C.S. Machtans, and S.J. Hannon. 1997. Are boreal birds resilient to forest fragmentation? An experimental study of short-term community responses. *Ecology* 78: 1914-1932.

Schmiegelow F.K.A., and S.J. Hannon. 1999. Forest-level effects of fragmentation on boreal songbirds: the Calling Lake Fragmentation Studies. Pp.201-221 *In* J. A. Rochelle, L. A. Lehmann and J. Wisniewski (eds.). Forest fragmentation: wildlife and management implications. Brill, Leiden, Netherlands .

StataCorp. 1999. *Stata Statistical Software*: Release 6.0 College Station, Texas: Stata Corporation.

Strong, W.L., and K.R. Leggat. 1981. *Ecoregions of Alberta*. Alberta Energy and Natural Resources Technical Report T/4. Edmonton, Alberta, Canada.

Vernier, P., and S.G. Cumming. 1998. Predicting landscape patterns from stand attribute data in the Alberta boreal mixedwood. Sustainable Forest Management Network Working Paper 1998-7**.**

Vernier, P., Schmiegelow, F.K.A., and Cumming, S.G. 2001. Modelling bird abundance from forest inventory data in the boreal mixedwood forests of Canada. In: Predicting Species Occurrences: Issues of Scale and Accuracy. Island Press, Washington D.C.