## Boreal Ecosystem Recovery and Assessment (BERA) – November 6, 2019 meeting, 11:15 AM – 12:00 PM

## Project Outline

|  |  |
| --- | --- |
| The value of high-density LIDAR data in predicting boreal bird species | |
| Lead | Name and affiliation of person primarily responsible: Lionel Leston [BERA, Bioacoustic Unit, University of Alberta] |
| Collaborators | * Gustavo Lopez Quieroz [BERA, University of Calgary] * Mustafizur Rahman [BERA, University of Calgary] * Silvia Alejandra Losada [BERA, University of Calgary] * Erin Bayne [BERA, Bioacoustic Unit, University of Alberta] * Julia Linke [BERA, University of Calgary] * Greg McDermid [BERA, University of Calgary] |
| Data Requirements | * Avian point count data (provided by the Bioacoustic Unit) * Coarse-scale habitat and footprint data (provided by the Alberta Biodiversity Monitoring Institute) * LIDAR point cloud data (provided by Greg McDermid and Mustafizur Rahman) * Coarse woody debris data (provided by Gustavo Lopez Quieroz) * Snag data (provided by Mustafizur Rahman [BERA, University of Calgary]) * Shrub structural (and floristic?) data (provided by Silvia Alejandra Losada) (IF AVAILABLE) |
| Project Dependencies & Contingency Plans | **Dependencies**:   * Transcription of remaining recordings from Kirby Grid (16 stations) * Habitat and human footprint for Kirby Grid (to be digitized by ABMI) * Point cloud layer (max veg ht., mean veg ht., pt hits on/near ground/at a certain height above ground (determine what scale of point cloud data, by next week) (available November 20) * Remote-sensing layers provided by Gustavo, Mustafiz, and Silvia (Coarse woody debris layer already available, snag data assumed to be ready, additional shrub layer may be available by March)   **Contingency Plans**:   * Alternate coarse layers available as rasters (Beaudoin layer) or with permission from Al-Pac, possibly Al-Pac AVI layer from 2016 * Base analyses just on the already transcribed station data (84 stations) |
| Deliverables | * Base model results (no fine-scale data) for 20 species of birds in different guilds or most common species (Nov 6) * Interim report (Dec 2019): models incorporating point cloud data, snags, coarse woody debris * Interim report (Mar 2019): models incorporating shrub layer (IF AVAILABLE) * Final report (May 2020) * Published paper (2020-2021) |
| Status | Start date: September 2019  Status: ongoing  Scheduled completion: May 2020 |

## Overview:

### Introduction: The structure of boreal forests in Alberta is changing with increasing forestry and energy sector development. There are much available vegetation and human footprint data at large extents within Alberta’s boreal forests for predicting the effects of human footprint on wildlife. These data include both shapefiles (e.g. Alberta Vegetation Inventory, Alberta Biodiversity Monitoring Institute wall-to-wall human footprint and vegetation layer) and remotely sensed data processed into rasters. However, these data are mainly available at a coarser scale of resolution (e.g. 250-m raster cells) or are summarized for shapefile polygons (e.g. stand type, % cover by dominant species in each stand). Many recent studies suggest that models of bird abundance are improved by including fine-scale vegetation structural data (e.g. crown height, canopy cover, shrub density) (Bayne, Haché, and Hobson 2010). However, fine-scale vegeation data collected from field surveys are time-consuming and labor-intensive to obtain even over small extents, and the improvement in model fit from including fine-scale data may be insufficient relative to the expended effort (Bayne, Haché, and Hobson 2010).

### Newer remote sensing techniques like LIDAR (Light Detection and Ranging) have become widespread and have been used to efficiently quantify fine-scale vegetation structure over large areas (). Some recent studies have employed LIDAR based vegetation metrics at point count locations to predict bird abundance, and these studies have found that incorporating LIDAR-based fine-scale vegetation structural variables into models improves predictions of bird abundance (e.g. Hinsley et al. 2002, Hill and Thompson 2005, Broughton et al. 2006, Boehlmann et al. 2007, Clawges et al. 2008, Graf et al. 2009, Martinuzzi et al. 2009, Muller et al. 2009, Goetz et al. 2010, Muller et al. 2010, Seavy et al. 2009, Lesak et al. 2011, Tattoni et al. 2012, Wilsey et al. 2012, Vogeler et al. 2013, Eldegard et al. 2014, Garabedian et al. 2014, Vierling et al. 2014). There are additional remotely sensed fine-scale non-LIDAR data such as coarse woody debris and snag densities that may improve predictions of ground-nesting and cavity-nesting species as well. As with LIDAR, these data products are efficiently obtained across large extents.

### Objectives: To model how well abundance of boreal bird species (species present at 10 % of sites) are predicted by different kinds of spatial data, from coarse-scale remotely sensed layers (e.g. Beaudoin layer []) and forest resource inventory shapefiles (e.g. Alberta Vegetation Inventory []) to fine-scale LIDAR point cloud data. We will also evaluate whether 1) models containing variables from multiple sources predict bird abundance better than models containing variables from a single data source; and 2) whether averaged predicted abundances of each species from all data sources are more accurate than predicted abundances of species based on a single data source. We predict that models based on or including fine-scale data collected by drones and planes (e.g. LIDAR-based point clouds, coarse woody debris, snags, possibly shrub density) will perform at least as well or better at predicting species abundance than models based only upon coarse-scale spatial data.

### Study Questions:

Are species associated with older forests and tree-nesting species more abundant/better predicted at sites with a higher density of LIDAR points at greater heights above ground?

Are shrub-nesting and ground-nesting species more abundant/better predicted at sites with a lower density of LIDAR points close to the ground.

Are shrub-nesting and ground-nesting species more abundant/better predicted at sites with a greater density of coarse woody debris.

Are cavity-nesting birds more abundant/better predicted at sites with a greater density of snags?

How does the abundance of different fine-scale vegetation metrics vary with the amount of, or distance from different kinds of human footprint, i.e. are the fine-scale vegetation metrics a potential mechanism through which human footprint affects the abundance of boreal birds?

## Study Site(s):

The “Kirby” grid ~45 minutes north of Calling Lake (UTMs: 489525-494943, 6131568-6136993). If similar coarse-scale and fine-scale remote-sensed data are available alongside point count data outside of the Kirby grid in Alberta’s boreal forest region, then a larger study area might be considered. We will be using indices of bird abundance from autonomous recording unit (ARU) stations, and individual recordings (3-4 per station) will be the unit of analysis. Data consists of counts of each species detected in each recording; actual abundance is not known but estimated.

## Study Species:

The 20 most common species, in terms of the number of stations with at least one detection of a given species, are: American Robin, Chipping Sparrow, Dark-eyed Junco, Golden-crowned Kinglet, Gray Jay, Hermit Thrush, Le Conte’s Sparrow, Lincoln’s Sparrow, Ovenbird, Palm Warbler, Pine Siskin, Red-breasted Nuthatch, Red-eyed Vireo, Ruby-crowned Kinglet, Swainson’s Thrush, White-throated Sparrow, White-winged Crossbill, Winter Wren, and Yellow-rumped Warbler. The least widespread of these species on the Kirby Grid was Red-breasted Nuthatch, detected at 10 of 84 stations with transcribed data. Other species of conservation interest (e.g. Black-throated Green Warbler, Brown Creeper, Canada Warbler) are either less widespread or were undetected at the Kirby grid.

Nine of the 20 species (Golden-crowned Kinglet, Gray Jay, Pine Siskin, Red-breasted Nuthatch, Ruby-crowned Kinglet, Swainson’s Thrush, White-winged Crossbill, Winter Wren, and Yellow-rumped Warbler) are associated with boreal forests older than 80 years and Ovenbirds are most abundant in mature boreal forests (~60-80 years old). These species would be predicted to be more abundant at sites with a greater density of LIDAR points higher above the ground. The remaining species are habitat generalists or associated with younger boreal forests. At least some of these species would be predicted to be more abundant at sites with a greater density of LIDAR points closer to the ground.

Five of the 20 species (Dark-eyed Junco, Le Conte’s Sparrow, Lincoln’s Sparrow, Ovenbird, Palm Warbler, White-throated Sparrow) are shrub or ground nesters whose numbers are predicted to be strongly related to the density of LIDAR points closer to the ground. Such species are also predicted to vary with the amount of coarse woody debris on the ground, given that the amount of coarse woody debris might influence the amount of other ground cover types (e.g. bare ground, herbaceous vegetation, woody vegetation).

Fifteen of the 20 species are tree-nesting species that are predicted to vary with the density of LIDAR points higher above the ground. One species (Red-breasted Nuthatch) is a cavity nester that is predicted to increase with the density of snags.

## Strategy:

September (Received bird data from 84 stations at Kirby grid; initial N-mixture model scripts developed; coarse woody debris layer received)

October 9 - meeting

October (Develop initial model scripts; acquire coarse-filter habitat and footprint data for base model; obtain snag data layer)

October 23 – interim meeting 11:30 Wed

Early November (Lionel: have base model ready and run model for 20 species, using just coarse-scale variables from ABMI; determine amount of spatial autocorrelation for each species to account for in analyses)

November 6 – present results from base model for ~20 species of the most common birds

November 20 (receive remaining remote-sensed layers: LIDAR-based point clouds from Mustafiz)

December (Lionel: add fine-scale data as it comes along to the base model)

January-March (initial results obtained; add additional point count data from Kirby grid as recordings are transcribed; maybe Silvia will have shrub data ready but don’t count on it)

May (final report)

Figure 1. Location of Kirby grid in Alberta. There are multiple BERA studies (different point colours) taking place on the Kirby grid. We will be using at least 84 of the 100 ARU stations (red points) in our analyses.



![A screenshot of a cell phone

Description automatically generated]()

## Methods:

### *Alberta Vegetation Inventory and human footprint data (shapefiles*): We obtained vegetation shapefile data from the Alberta Vegetation Inventory and human footprint shapefile data from Alberta Biodiversity Monitoring Institute. Both kinds of data were extracted to point counts at two spatial scales (150 m or local scale, and 1 km or landscape scale) that have been used in previous regional species distribution models of Alberta boreal forest birds (Sólymos et al. 2015, Ball et al. 2016). These variables will be used to create a base model for each species. Such variables can include the dominant stand type or land use at local scale, forest age at local scale, and the proportions of different individual or combined land uses within 1 km. The variables selected for analysis will be based on previous ABMI/BAM/ECCC models for the 20 study species.

### *Remote-sensing vegetation and human footprint data (rasters*): We used vegetation, terrain, water, and human footprint data as predictors of boreal forest bird species abundance. Vegetation layers were based on remotely sensed national data for Canada at 250-m resolution, described in Beaudoin et al. (2013). Vegetation predictors included the proportion of each cell dominated by different tree species, all broadleaf species combined, and all needle-leafed species combined; the biomass attributed to branches, foliage, stem bark, stem wood, total dead vegetation, total live above-ground vegetation, stand age, crown closure, stand height; vegetated and non-vegetated land cover; treed and non-treed vegetated cover (Table 1). We used a provincial water layer to quantify the amount of water associated with rivers, ponds, lakes, and wetlands in general in Alberta (Table 1). We used several terrain variables at 100-m resolution that were suggested by past studies as being important in determining ecosystem structure and hence habitat variables for birds (Stralberg et al. 2018). These terrain variables are related to the underlying rock layers (“surficial geology”, “bedrock geology”) which influence soil structure and nutrient availability for plants and animals; ruggedness (“Alberta digital elevation model 100-m”, “elevation residuals”, “compound topographic index” [Sappington et al. 2007], “topographic position index averaged within 300 m”, “topographic position index averaged within 2 km” [Gallant and Wilson 2000, De Reu et al. 2013], “terrain ruggedness index” [Riley et al. 1999], “vector ruggedness index averaged within a 5x5 cell grid”, “vector ruggedness index within 11x11 cell grid” [Gessler et al. 2005]), which influences the direction of water flow and wetness; and the amount of insolation and warmth at a site (“heatld3class”, “slope”, “slope aspect”, “solar flux”) (Table 1). Human footprint predictors (cropland, industrial sites, mine sites, pipelines, hard road surfaces, narrow seismic lines, wide seismic lines, transmission lines) were derived from a provincial layer produced by the Alberta Biodiversity Monitoring Institute (Table 1).

We used a Gaussian filter (focalweight function in raster package [Hijmans and van Etten 2012]) to characterize vegetation and terrain variables at larger scales, with 250 m and 750 m selected as the distances for defining our filters. Gaussian filters differ from traditional GIS buffers in that features are weighted according to feature distance from point counts and the amount of weight is described by a Gaussian function, with more distant features carrying gradually less weight. Gaussian functions are partially defined by a distance value that determines when weights strongly decrease, and a Gaussian function with a larger distance threshold is analogous to a GIS buffer with a larger radius. However a traditional GIS buffer would assign equal weight to all examples of a feature within the buffer radius whether or not those features are next to a point count or at the buffer periphery, and a traditional GIS buffer assigns very different weights to features that are just barely located on either side of a buffer boundary, which is unrealistic (Chandler and Hepinstall-Cymerman 2016) (Table 1).

Table 1. Predictors from remote-sensed data (Beaudoin 2013) used in mixture models of boreal bird abundance within a grid of autonomous recording unit point count stations in northern Alberta, 2018-2019. X indicates if a given predictor’s effect was analyzed at a particular spatial scale (cell-based or local; 250-m and 750-m filter or landscape).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Predictor | Source | Unit of Measurement | 250-m cell | 250-m filter | 750-m filter |
| *Abies balsamifera* (Species\_Abie\_Bal) | Beaudoin | % | X | X | X |
| *Abies lasiocarpa* (Species\_Abie\_Las) | Beaudoin | % | X | X | X |
| *Acer negundo* (Species\_Acer\_Neg) | Beaudoin | % | X | X | X |
| *Alnus* spp. (Species\_Alnu\_Spp) | Beaudoin | % | X | X | X |
| *Betula papyrifera* (Species\_Betu\_Pap) | Beaudoin | % | X | X | X |
| *Larix lariciana* (Species\_Lari\_Lar) | Beaudoin | % | X | X | X |
| *Picea engelmanni* (Species\_Pice\_Eng) | Beaudoin | % | X | X | X |
| *Picea glauca* (Species\_Pice\_Gla) | Beaudoin | % | X | X | X |
| *Picea mariana* (Species\_Pice\_Mar) | Beaudoin | % | X | X | X |
| *Pinus alba* (Species\_Pinu\_Alb) | Beaudoin | % | X | X | X |
| *Pinus banksiana* (Species\_Pinu\_Ban) | Beaudoin | % | X | X | X |
| *Pinus contorta* (Species\_Pinu\_Con) | Beaudoin | % | X | X | X |
| *Pinus ponderosa* (Species\_Pinu\_Pon) | Beaudoin | % | X | X | X |
| *Populus balsamifera* (Species\_Popu\_Bal) | Beaudoin | % | X | X | X |
| *Populus tremuloides* (Species\_Popu\_Tre) | Beaudoin | % | X | X | X |
| *Prunus pensylvanicus* (Species\_Prun\_Pen) | Beaudoin | % | X | X | X |
| *Pseudotsuga mensiezii* (Species\_Pseu\_Men) | Beaudoin | % | X | X | X |
| *Salix* spp. (Species\_Sali\_Spp) | Beaudoin | % | X | X | X |
| SpeciesGroups\_Broadleaf | Beaudoin | % | X | X | X |
| SpeciesGroups\_Needleleaf | Beaudoin | % | X | X | X |
| Structure\_Biomass\_Branch | Beaudoin | Numeric | X | X | X |
| Structure\_Biomass\_Foliage | Beaudoin | Numeric | X | X | X |
| Structure\_Biomass\_StemBark | Beaudoin | Numeric | X | X | X |
| Structure\_Biomass\_StemWood | Beaudoin | Numeric | X | X | X |
| Structure\_Biomass\_TotalDead | Beaudoin | Numeric | X | X | X |
| Structure\_Biomass\_TotalLiveAboveGround | Beaudoin | Numeric | X | X | X |
| Structure\_Stand\_Age | Beaudoin | Numeric | X | X | X |
| Structure\_Stand\_CrownClosure | Beaudoin | Numeric | X | X | X |
| Structure\_Stand\_Height | Beaudoin | Numeric | X | X | X |
| LandCover\_NonVeg | Beaudoin | % | X | X | X |
| LandCover\_Veg | Beaudoin | % | X | X | X |
| LandCover\_Veg\_Treed | Beaudoin | % | X | X | X |
| LandCover\_VegNonTreed | Beaudoin | % | X | X | X |
| CompoundTogographicIndex | Terrain Layer | % | X | X | X |
| CultivationCrop | ABMI Human Footprint Layer | % | X |  |  |
| IndustrialSiteRural | ABMI Human Footprint Layer | % | X |  |  |
| MineSite | ABMI Human Footprint Layer | % | X |  |  |
| Pipeline | ABMI Human Footprint Layer | % | X |  |  |
| RoadHardSurface | ABMI Human Footprint Layer | % | X |  |  |
| SeismicLineNarrow | ABMI Human Footprint Layer | % | X |  |  |
| SeismicLineWide | ABMI Human Footprint Layer | % | X |  |  |
| TransmissionLine | ABMI Human Footprint Layer | % | X |  |  |
| Water | Water Bodies Layer | % | X | X | X |
| "ab100m\_dem" (Alberta Digital Elevation Model 100-m resolution) | Terrain Layer | Numeric | X | X | X |
| "aggregates" (Aggregate Materials, e.g. sand, gravel) | Terrain Layer | Numeric | X | X | X |
| "dunes" (Dunes) | Terrain Layer | Numeric | X | X | X |
| "elevresid" (Elevation Residuals) | Terrain Layer | Numeric | X | X | X |
| "geol\_bedrck" (Bedrock Geology) | Terrain Layer | Numeric | X | X | X |
| "geol\_surf" (Surficial Geology) | Terrain Layer | Numeric | X | X | X |
| "heatld3clss" (Heat Load 3 Classes) | Terrain Layer | Numeric | X | X | X |
| "slope" (Slope) | Terrain Layer | Numeric | X | X | X |
| "slpasp" (Slope Aspect Solar Radiation Index) | Terrain Layer | Numeric | X | X | X |
| "solar\_flux" (Solar Flux) | Terrain Layer | Numeric | X | X | X |
| "tpi2km" (Topographic Position Index 2 km radius) | Terrain Layer | Numeric | X | X | X |
| "tpi300m" (Topographic Position Index 300 m radius) | Terrain Layer | Numeric | X | X | X |
| "tri" (Terrain Ruggedness Index) | Terrain Layer | Numeric | X | X | X |
| "vrm11x11" (Vector Ruggedness Index 11x11 cell grid) | Terrain Layer | Numeric | X | X | X |
| "vrm5x5" (Vector Ruggedness Index 5x5 cell grid) | Terrain Layer | Numeric | X | X | X |

### *LIDAR and other fine-scale data*: These data will consist of the number or proportion of point returns within different height intervals collected when scanning the Kirby Grid, e.g. within 0-1, 1-3, 3-10, and >10 m above the ground or at ~1-m intervals (Lesak et al. 2011). The density of point returns within lower height intervals can be used to indicate shrubby understory (Wilsey et al. 2012), while point return density in greater height intervals can indicate canopy vegetation (Vogeler et al. 2013). The raw point returns can then be summarized at two spatial scales. First, the points can be summarized within a fine-resolution raster layer like an intermediate digital elevation/terrain/surface model (e.g. 1-2 m to distinguish individual shrubs) to identify denser spots and gaps in canopy vegetation and shrubby understory (Broughton et al. 2006, Boehlmann et al. 2007, Graf et al. 2009, Eldegard et al. 2014, Garabedian et al. 2014). Second, the resulting raster layer can be summarized within a buffer zone around each point count to provide estimates of heterogeneity in canopy cover, shrub understory, or vegetation density (Lesak et al. 2011, Vogeler et al. 2013, Vierling et al. 2014). Previous studies have summarized LIDAR data at the extent of a study species’ territory size or found that different species responded most strongly to LIDAR variables at a variety of spatial scales. Thus, our LIDAR data will be summarized at 3 scales around each point count (50 m, 150 m, 500 m), to determine at which spatial scale different bird species are best predicted by LIDAR data. Based on territory sizes reported in the literature, Gray Jays are predicted to respond most strongly at the 500-m scale (Bowman 2003); Chipping Sparrow, Red-breasted Nuthatch, and Winter Wren are predicted to respond most strongly at the 150-m scale (Odum et al. 1955, Matthysen et al. 1992, Toews and Irwin 2008); and the remaining species are predicted to respond most strongly to LIDAR data at the 50-m scale (Morse 1976, Wasserman 1980, Chandler et al. 1994, Wortman-Wunder 1997, Evans et al. 2000, Bowman 2003, Bourque and Desrochers 2006).

Other types of fine-scale vegetation data are available for the Kirby grid, including photogrammetry data for coarse woody debris volume and perhaps eventually shrub understorey. Coarse woody debris volume is a metric currently available as a 100-m raster layer for the Kirby grid. There is also a shapefile layer derived from the same data source in which logs and snags are distinguished from each other, with the snag data being considered more accurate than the log data, since many logs are likely to be concealed by canopy vegetation.

### *Bird Data*: We used autonomous recording units (ARUs: Model SM4, Wildlife Acoustics Inc., Maynard, MA; firmware version XXX) to generate repeated point counts of bird abundance at the Kirby Grid in the summer of 2018. Point count stations were 600 m apart within a 10x10 grid. At each station location, field technicians located a tree that was large and strong enough to support the weight of an ARU screwed into the trunk on the north side of the tree, but whose diameter at breast height (~1.5 m) was small enough (~15 cm or less) that the trunk did not block the microphones on either side of the ARU from picking up sounds on the south side of the tree. Each ARU was attached at about breast height (~1.5 m) to the tree and was programmed to turn on for at least one 5-minute recording each day around sunrise (4:52 AM – 5:06 AM local time) until the ARU was either retrieved and returned to the lab or redeployed to another station location. When retrieved or redeployed, all recordings from a given location were stored within 1 or more SD cards inside the ARU: these SD cards were replaced with new cards if the ARU was redeployed to another location in the same season. We used recordings from May 20 to July 11 in our analyses. In the lab, field technicians listened to recordings and transcribed the number of distinct individuals heard from each species as a measure of abundance counted within each station visit. Technicians also recorded the date and time of day of individual recordings and estimated qualitative values of environmental variables within the recordings such as the strength of wind, rain, or environmental noise, which affect the probability of detecting birds that are present. Up to 4 recordings per station that did not have excessive noise from wind, rain or other environmental noise were randomly selected and transcribed for the analyses in this paper.

### *Analysis*: Multiple recordings of soundscapes at the ARU locations are similar to point counts that are visited multiple times to collect data of bird species abundance or occupancy. Counts or detections of birds during point counts or within recordings are indices of true abundance or occupancy, since the probability of detecting a species that is present at a site is <1 (Anderson 2001), due to environmental variables (detection covariates) affecting sound detection by humans (e.g. environmental noise, sound attenuation by vegetation [Buckland et al. 2005]) or singing activity by birds (weather, time of breeding season, time of day [Farnsworth et al. 2002]). If probability of detection is not accounted for, then estimates of relative abundance or occupancy from raw counts or detections will be biased (Royle and Nichols 2005). *N*-mixture and occupancy models are types of hierarchical models in which the number of birds counted is a function of two processes: those variables that affect abundance (lambda λ) or occupancy (psi ψ) of birds at sites; then, given that a species is present at a site, the probability of detecting that species due to detection covariates (Kéry et al. 2005). Analyses involving *N*-mixture and occupancy models require multiple survey visits per survey location, in which covariates affecting detection probability can vary across visits while covariates affecting abundance and occupancy vary across survey locations.

Statistical assumptions of the most basic *N*-mixture and occupancy models include 1) population closure, i.e. animal numbers do not change during the survey period due to births, deaths, immigration or emigration, and 2) independence of survey locations. Since survey points in our study are located in a grid, abundance or occupancy is likely to be more strongly correlated at points closer to each other in space, violating the second assumption. We accounted for spatial autocorrelation by running *N*-mixture models in the hSDM package in R (Vieilledent et al. 2015), which uses a conditional autoregressive (CAR) correlation structure to account for spatial correlation, i.e. observations are correlated with each other when they occur at less than a threshold or neighborhood distance from each other. To determine an appropriate neighborhood distance for specifying the amount of spatial autocorrelation in our models, we first ran regressions of the mean count of each species across each station’s visits, using the predictors of λ in our N-mixture models. These regressions were run as generalized least-squares models using the gls function in the nlme package in R (Pinhiero et al. 2017), and we generated variograms for the model residuals for each species. We assessed how pairwise variance in residuals changed with distance between stations and at what distance pairwise variance no longer increased, i.e. spatial autocorrelation became insignificant. This distance was used to determine an appropriate neighborhood distance for accounting for spatial autocorrelation in models of each bird species. Point count stations within this neighborhood distance are treated as being correlated and assigned equal weights when estimating effects of predictors on bird abundance, while point counts beyond the neighborhood distance are treated as independent and have zero influence on predictors of bird abundance within the neighborhood. The spatial panel models keep track of each point count’s influence on other stations using a spatial weights matrix.

Alberta Vegetation Inventory model: We used the following variables as predictors of bird abundance at stations:

Beaudoin layer model: We used the following variables as predictors of bird abundance at stations:

LIDAR model: We used the following variables as predictors of bird abundance at stations:

Averaging predictions from the separate models: We obtained estimated abundance of each species at each station from the AVI, Beaudoin, and LIDAR-based vegetation models and compared estimated abundance against the maximum count of each species at each station, to assess how well models based on different kinds of GIS data predicted species counts at each station. We then calculated an average predicted abundance for each species at each station from the 3 kinds of predictions based on AVI, Beaudoin, and LIDAR-based vegetation models, to see if the average prediction performed better than the individual model predictions.

Combining predictors from different GIS data: For each species, we identified the predictors with the strongest influence on bird abundance at each station by generating 95 % confidence intervals for the point estimates of each predictor. We selected those predictors from each model whose confidence interval limits were both negative or both positive and excluded zero. We then combined these predictors in a fourth N-mixture model for each species to determine if combining predictors from different kinds of GIS data resulted in more accurate predictions of species.

## Storyline:

Boreal forest bird communities are difficult to monitor effectively because much of their habitat is not easily accessible, especially since multiple visits to each survey point are necessary to accurately quantify bird abundance or occupancy as well as habitat features influencing abundance or occupancy. However, quantification of bird and habitat data in remote areas can be achieved efficiently for large numbers of sites by a combination of 1) remote sensing with drones or planes to collect fine-scale habitat data, and 2) use of programmable acoustic recorders or autonomous recording units to collect bird data over multiple recordings in place of human visits. Newer analysis techniques like *N*-mixture or occupancy models are then well-suited for estimating true abundance or occupancy of bird species at sites from multiple recorded visits while accounting for detection probability of each species on different visits due to weather, time of season and day, and environmental noise.

**Constraints, limitations, things to be aware of:**

Unless certain conditions are met (distances to individual birds in the recordings are known or can be estimated, either from noise levels, triangulation by closely-spaced ARUs, or simultaneous point count data collected by human observers with distance-sampling methods), point count data collected by ARUs can only provide measures of relative abundance, not densities of birds. The point counts in the Kirby grid are spaced 600 m apart, so cannot be used to triangulate bird locations and distances from ARUs. There are also no corresponding human observations of birds at the ARUs to use for estimating distances to birds. forest bird communities are difficult to monitor effectively because much of their habitat is not easily accessible, especially since multiple visits to each survey point are necessary to accurately quantify bird abundance or occupancy as well as habitat features influencing abundance or occupancy. Finally, counts of birds within ARU recordings are reliant on detection of bird sounds, so quietly or infrequently vocalizing bird species are less likely to be detected, and birds that are seen rather than heard will not be detected within recordings.

Eighty-four ARU point count stations and 3-4 recordings per ARU are currently available for analysis. This sample size will probably be insufficient for rarer species of interest such as owls, and some species of interest (e.g. Canada Warbler) have not been detected in the recordings transcribed so far.

## Literature Cited:

Anderson, D. R. (2001). The need to get the basics right in wildlife field studies. Wildlife Society Bulletin, 29, 1294-1297.

Ball, J. R., P. Sólymos, F. K. A. Schmiegelow, S. Haché, J. Schieck, and E. M. Bayne. 2016. Regional habitat needs of a nationally listed species, Canada Warbler Cardellina canadensis, in Alberta, Canada. Avian Conservation and Ecology 11(2):10.

Bayne, E. M., S. Haché, and K. A. Hobson. 2010. Comparing the predictive capability of forest songbird habitat models based on remotely sensed versus ground-based vegetation information. Canadian Journal of Forest Research 40: 65-71. Doi:10.1139/X09-170

Beaudoin, A., P. Y. Bernier, L. Guindon, P. Villemaire, X. J. Guo, G. Stinson, T. Bergeron, S. Magnussen, and R. J. Hall. 2013. Mapping attributes of Canada’s forests at moderate resolution through kNN and MODIS imagery. Canadian Journal of Forest Research 44: 521–532.

Boehlmann et al. 2007. Multi-trophic invasion resistance in Hawaii: bioacoustics, field surveys, and airborne remote sensing. Ecological Applications 17:2137-2144.

Bourque and Desrochers. 2006. Spatial Aggregation of Forest Songbird Territories and Possible

Implications for Area Sensitivity. Avian conservation and ecology 1, no. 2.

Bowman, J. 2003. Is dispersal distance of birds proportional to territory size? Canadian Journal of Zoology, 2003, 81(2): 195-202, https://doi.org/10.1139/z02-237.

Broughton, R.K., Hinsley, S.A., Bellamy, P.E., Hill, R.A. & Rothery, P. 2006. Marsh Tit Poecile palustris territories in a British broad-leaved wood. Ibis 148: 744–752. doi: 10.1111/j.1.

Buckland, S. T., D. R. Anderson, K. P. Burnham, and J. L. Laake (Editors) (2005). Distance Sampling. John Wiley & Sons, Ltd.

Chandler et al. 1994. Effects of testosterone on spatial activity in free-ranging male dark-eyed juncos, Junco hyemalis. Animal Behaviour 47: 1445-1455.

Chandler, R. and J. Hepinstall-Cymerman. 2016. Estimating the spatial scales of landscape effects on abundance. Landscape Ecology 31:1383-1394.

Clawges, R., Vierling, K., Vierling, L. & Rowell, E. 2008. The use of airborne lidar to assess avian species diversity, density, and occurrence in a pine/aspen forest. Remote. Sens. Envi

Eldegard et al. 2014. Modelling bird richness and bird species presence in a boreal forest reserve using airborne laser-scanning and aerial images. Bird Study 61(2)

Evans et al. 2000. Swainson’s Thrush (Catharus ustulatus). In A. Poole and F. Gill, eds. The Birds of North America, No. 540. The Birds of North America, Inc., Philadelphia, PA.

Farnsworth, G. L., Pollock, K. H., Nichols, J. D., Simons, T. R., Hines, J. E., & Sauer, J. R. (2002). A removal model for estimating detection probabilities from point-count surveys. The Auk, 119, 414-425.

Garabedian et al. 2014. Quantitative analysis of woodpecker habitat using high-resolution airborne LiDAR estimates of forest structure and composition. Remote Sensing of Environment

145: 68-80.

Goetz et al. 2010. Lidar remote sensing variables predict breeding habitat of a Neotropical migrant bird. Ecology, 91(6), 2010, pp. 1569–1576.

Graf, R.F., Mathys, L. & Bollmann, K. 2009. Habitat assessment for forest dwelling species using LiDAR remote sensing: Capercaillie in the Alps. Forest Ecol. Manag. 257:

Hijmans, R. J., and J. van Etten. 2012. raster: Geographic analysis and modeling with raster data. R package version 2.0-12. http://CRAN.R-project.org/package=raster.

Hill and Thompson 2005. Mapping woodland species composition and structure using airborne spectral and LiDAR data. International Journal of Remote Sensing, 26:17, 3763-3779.

Hinsley et al. 2002. Quantifying woodland structure and habitat quality for birds using airborne laser scanning. Functional Ecology 16: 851–857

Kéry, Marc, J. Andrew Royle, and Hans Schmid. 2005. Modeling avian abundance from replicated counts using binomial mixture models. Ecological applications 15: 1450-1461.

Lesak, A.A., Radeloff, V.C., Hawbaker, T.J., Pidgeon, A.M., Gobakken, T. & Contrucci, K. 2011. Modeling forest songbird species richness using LiDAR-derived measures of fo Remote Sensing of Environment 115(11): 2823-2835.

Matthysen et al. 1992. Is Social Organization in Winter Determined by Short- or Long-Term Benefits? A Case Study on Migrant Red-Breasted Nuthatches Sitta canadensis. Ornis Scandinavica 23: 43-48

Morse, D. M. 1976. Variables Affecting the Density and Territory Size of Breeding Spruce-Woods Warblers. Ecology, Vol. 57, No. 2 (Mar., 1976), pp. 290-301

Muller et al. 2009. Using airborne laser scanning to model potential abundance and assemblages of forest passerines. Basic and Applied Ecology 10: 671-681

Muller et al. 2010. Composition versus physiognomy of vegetation as predictors of bird assemblages:The role of lidar. Remote Sensing of Environment 114: 490–495

Odum, E. P. and E. J. Kuenzler. 1955. Measurement of Territory and Home Range Size in Birds. The Auk, Vol. 72, No. 2 (Apr., 1955), pp. 128-137

Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., Heisterkamp, S., Van Willigen, B., & Maintainer, R. (2017). Package ‘nlme’. Linear and Nonlinear Mixed Effects Models, version, 3-1.

Royle, J.A., J.D. Nichols, and M. Kéry. 2005. Modelling occurrence and abundance of species when detection is imperfect. Oikos 110: 353-359.

Seavy et al. 2009. Riparian bird response to vegetation structure: a multiscale analysis using LiDAR measurements of canopy height. Ecological Applications 19(7): 1848–1857.

Sólymos, P., L. Mahon, T. Fontaine, and E. M. Bayne. 2015. Predictive models for estimating the cumulative effects of human development on migratory landbirds in the oil sands areas of Alberta. Technical Report, Joint Oil Sands Monitoring: Cause-Effects Assessment of Oil Sands Activity on Migratory Landbirds, Edmonton, AB, Canada.

Tattoni et al 2012. Can LiDAR data improve bird habitat suitability models? Ecological Modelling 245: 103– 110.

Toews and Irwin 2008. Cryptic speciation in a Holarctic passerine revealed by genetic and bioacoustic analyses. Molecular Ecology, 17(11), 2691-2705.

Vieilledent, G., Merow, C., Guélat, J., Latimer, A.M., Kéry, M., Gelfand, A.E., Wilson, A.M., Mortier, F. and Silander Jr, J.A., 2015. Hierarchical Bayesian species distribution models with the hSDM R Package.

Vierling et al. 2014. How much does the time lag between wildlife field-data collection and LiDAR-data acquisition matter for studies of animal distributions? A case study using bird communities. Remote Sensing Letters, 5:2, 185-193.

Vogeler et al. 2013. Lidar-Derived Canopy Architecture Predicts Brown Creeper Occupancy of Two Western Coniferous Forests. Condor 115: 614–622

Wasserman, F. E. 1980. Territorial Behavior in a Pair of White-Throated Sparrows. Wilson Bulletin 92: 74-87.

Wilsey et al. 2012. Performance of habitat suitability models for the endangered black-capped vireo built with remotely-sensed data.

Wortman-Wunder, E. 1997. Territory Size in Lincoln's Sparrows (Melospiza lincolnii). The Southwestern Naturalist 42: 446-453