



bioacoustic unit

Habitat selection at different scales for a declining aerial insectivorous bird as determined by autonomous recording technology

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(Image Retrieved From: [https://www.theguardian.com/science/grrlscientist/2012/aug/23/1](https://www.theguardian.com/science/grrlscientist/2012/aug/23/))

Bioacoustic Unit

The Bioacoustic Unit is a collaboration between the Bayne Lab at the University of Alberta and the Alberta Biodiversity Monitoring Institute . The Bioacoustic Unit is the authority on best practices for using acoustic technology in the province and a leader in the application of wildlife acoustic data to environmental management and research needs. In addition, our team is actively engaged in research to enhance our methodologies and advance our tools to better understand our natural acoustic environment. Clients regularly partner with us to assist with their wildlife monitoring needs. Our involvement varies from client to client and spans the full range of services from simply providing information to conducting a full research project on their behalf.

Our services include:

Listening

We can collect the data you need, or help you do it yourself. We provide 'how to' protocols that will guide you through the process of deploying, programming, and retrieving your audio data. Or, let us do it for you!

Analyzing

We have a team of expert taxonomists that will translate your audio recordings into species identifications. In addition, our researchers have developed automatic recognizers that quickly process audio files to detect multiple species of conservation concern. We encourage all clients to contribute their data to our publicly available data set. However, we understand that some clients may be bound by confidentiality issues that preclude this. The Bioacoustic Unit is therefore flexible in how raw data is disseminated.

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Abstract

Conservation management is impeded by the lack of baseline data for many non-passerine, cryptic, or nocturnal species that are inadequately sampled by traditional monitoring programs. The recent rise of bioacoustic technology, including autonomous recording units (ARUs) and automated signal recognition software provide an opportunity to use archived bioacoustic datasets to fill baseline data gaps for rare and/or nocturnal species. We extracted detections from a large bioacoustic database using automated signal recognition software and boosted regression tree models to build regional home range selection and territory selection models for the Common Nighthawk (*Chordeiles minor*), a declining aerial insectivore for which there is minimal existing data. We found Common Nighthawk home range selection and territory selection to be explained by different environmental variables. Home range selection was primarily explained by landscape scale geographic and climate variables and some avoidance of wetland areas. Territory selection was also strongly influenced by landscape scale climate variables, proportion of seismic lines, and areas with minimal poor fen. Mean January temperatures and the proportion of pine forest were the only environmental variables that had relative influence (>3.5) for both home range and territory selection, with the marginal effect of pine forest increasing sharply after a threshold of approximately 30% pine in the surrounding 3 km for both selection models. The importance of landscape scale variables relative to local scale variables was higher for both home range and territory selection, although the magnitude of importance of landscape scale variables was higher for home range selection. Our results provide wildlife managers with guidance on where Common Nighthawks may be found in the boreal forest during the breeding season, with selection for cold, dry, northern landscapes, pine forests, and avoidance of wetland areas which is contrary to results for other biomes. The strong influence of landscape scale variables emphasizes the importance of landscape scale conservation for highly-mobile species with large home ranges. Our case study also highlights the value of archived bioacoustic datasets for conservation of understudied species.

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Introduction

Ecological monitoring is imperative for the management of wildlife populations, but species with cryptic or nocturnal life histories create logistical complications for surveys. As a result, there is a lack of information about some wildlife populations in Canada, which in turn hinders effective wildlife management and conservation. The use of habitat selection models to delineate critical habitat (i.e., habitat essential for species conservation) is one of the core tools of federal species at risk legislation in Canada and the US (Hagen & Hodges 2006); however, defining critical habitat requires, at minimum, information on the basic habitat associations of the species of interest (Rosenfeld & Hatfield 2006).

Recently, bioacoustic technology has presented an alternative data collection method for obtaining baseline data on understudied species, which can then be used to study habitat associations (Blumstein et al. 2011; Shonfield & Bayne 2017). Autonomous recording units (ARUs) are self-contained audio recording devices that can be deployed in remote locations and programmed to collect time-series data at any time of day for long periods of time. The acoustic recordings collected by ARUs can then be processed by automated signal recognition software (hereafter “recognizer”) to build a baseline dataset of detections for a target species (de Oliveira et al. 2015; Katz et al. 2016).



(Knight, 2017)



(Upham-Mills, 2017)

Using ARUs for biological monitoring and research has many benefits, including the collection of permanent acoustic recordings that can be archived and used to study other species or ecological phenomena at a later date. The Common Nighthawk (*Chordeiles minor*) presents an ideal opportunity to use archived ARU data for baseline dataset development. The crepuscular nature of the Common Nighthawk precludes individuals from detection on most traditional point count surveys (Environment Canada 2016), yet their simple, consistent, and frequent calls make them highly detectable with automated signal recognition software (Knight et al. in prep). Furthermore, the Common Nighthawk is one of the least understood bird species in North America and is listed as 'Threatened' under Canada's Species at Risk Act due to steep population declines (Environment Canada 2016). Initial national habitat models using existing sparse baseline data suggest the boreal forest may support particularly dense populations in Canada (Hache et al. 2014); however, the ecology and habitat associations of Common Nighthawks in the boreal forest are almost entirely unknown (Brigham et al. 2011).

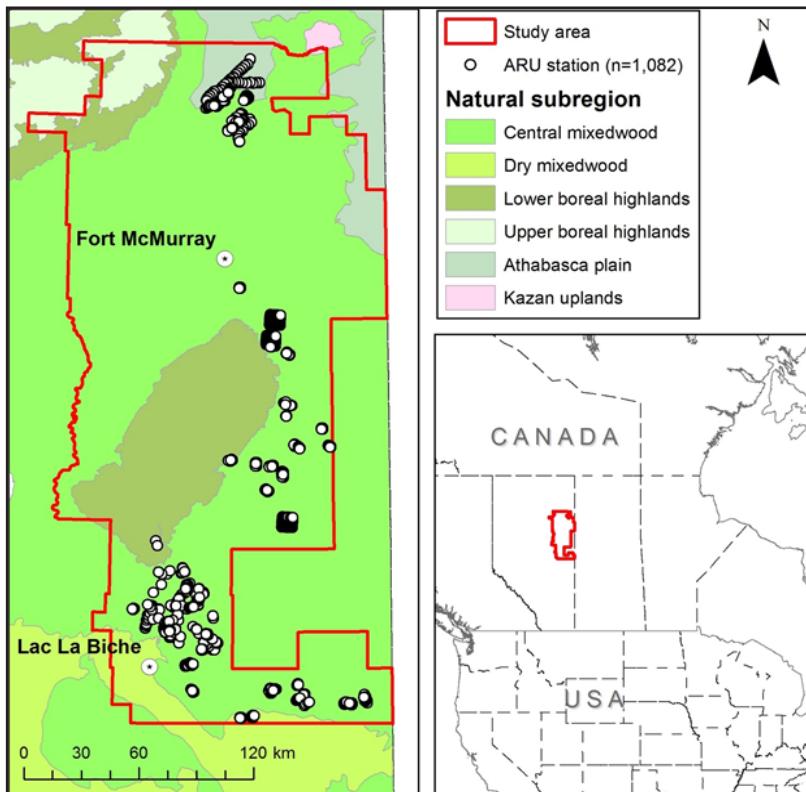
We used recognizer data from six bioacoustic projects conducted in 2015 in northeastern Alberta's boreal forest to build the first predictive habitat model for Common Nighthawks in the boreal forest. First, we built a baseline data set for northeastern Alberta by extracting Common Nighthawk detections from over 200,000 ARU recordings collected in 2015 using automated signal recognition

software. Next, we characterized the environmental variables at each of the 1,082 ARU locations at a local and a landscape scale from a variety of remote sensing datasets. We used boosted regression tree models to examine which environmental variables explained variation in home range habitat selection and territory habitat selection. We predicted that Common Nighthawks would select for different environmental variables at the home range and territory scales, and that environmental variables at the landscape (3 km) scale would have a stronger relative influence on home range selection than local (300 m) variables, while local variables would have a stronger relative influence on territory selection.

Methods

Study Area

We defined our study area in northeastern Alberta as a 4,700 km² area within Alberta's Lower Athabasca Planning Region (LAPR), which included the sampling locations of most of the six archived bioacoustic projects (Figure 1). The study area was primarily within the Central Mixedwood Natural Subregion (Natural Regions Committee 2006) and the boreal plains ecozone (Marshall et al. 1999). The landscape was characterized by a mosaic of upland forest types, lowland peat bogs, and fens. At the time of study, the region was subject to frequent and widespread disturbance, including active forestry, oil and gas development, and wildfire.



(Image Retrieved From: <http://www.ramp-alberta.org/river/boreal/canada.aspx>)

Figure 1. Locations of archived autonomous recording units (ARU) used for Common Nighthawk habitat modelling in northeastern Alberta, Canada.

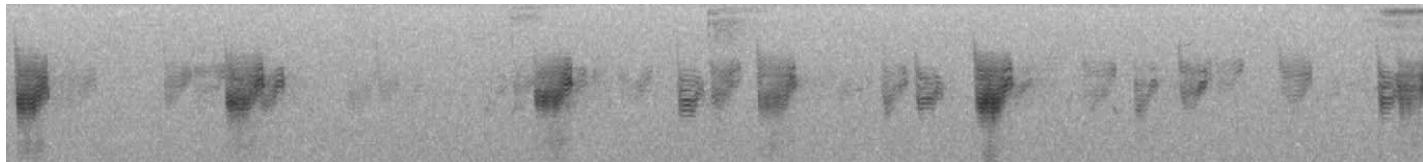
Acoustic Data Collection

We selected acoustic data collected by ARUs (SM2, SM2+, and SM3; Wildlife Acoustics Inc.) across six different projects at 1,081 ARU stations (Appendix 1). Technicians deployed all ARUs according to a standardized protocol (Lankau 2015) between June 1 and July 31, 2015 for a minimum of two days at each site. The recording schedule varied across the six projects, but all recordings were 10 minutes (Appendix 1). We used Song Scope (Wildlife Acoustics 2011) software to extract Common Nighthawk detections from ARU recordings. We created a recognizer by training Song Scope with high quality clips of 138 Common Nighthawk calls collected from northeastern Alberta and south-central British Columbia. We used the recognizer to scan the recordings from all projects using a minimum score threshold of 70 and a minimum quality threshold of 30. We selected a minimum score threshold of 70 to minimize the number of false positive detections and to limit the detection radius at each ARU station to approximately 300 m to avoid overlap between adjacent ARU stations (unpublished data). We have previously found that presence-absence recall of the recognizer at a score threshold of 70 is approximately 70% per recording (see Knight et al. in review a for details), with the remaining 30% likely explained by a difference in detection radius between the recognizer and a human listener. We then visually verified all potential Common Nighthawk detections identified by Song Scope to confirm whether they were true or false hits.

Environmental Data Collection

We extracted 60 environmental variables for each ARU station and 789 random points with the LAPR from seven remotely sensed datasets (Appendix 2). We chose the avian habitat classification dataset for all upland variables because it provided information on both dominant tree type and major seral stage (Martin-Demoor & Mahon 2014). We chose an enhanced wetland classification dataset for lowland variables including major wetland types because it has high accuracy for peat wetland classification (Ducks Unlimited Canada 2011). We chose the human footprint inventory (Alberta Biodiversity Monitoring Institute 2014) because it was available as hand delineated vector layers. Finally, we also included variables from the soil landscapes of Canada database (Schut et al. 2011), a derived light detection and ranging (LiDAR) dataset for vegetation structure (Coops et al. 2016), climate surfaces (Hamann et al. 2013), and the natural subregions classification system (Natural Regions Committee 2006).

We extracted each variable with one of several methods depending on the data type (categorical or continuous). We extracted all categorical raster or polygon variables as proportions within a specified radius and all continuous raster variables as the mean value within a specified radius. The exception was natural subregion, northing, and easting, which we calculated as single values at the ARU station.



(Knight, 2017)



For variables measured within a specified radius, we extracted features at two scales. We defined the local scale as a 300 m radius surrounding each ARU station because 300 m is the approximate detection radius of the recognizer and radius of a Common Nighthawk territory (unpublished data). We defined the landscape scale as a 3 km radius surrounding each ARU station because it was an order of magnitude larger than the local scale and members of the nightjar family are known to forage at least 3 km from their territory (Armstrong 1965; Brigham 1989; Brigham et al. 2011). We did not extract variables at the territory scale for datasets with a raster cell size greater than the territory scale radius, or extract variables that covaried (correlation coefficient > 0.9; 300 m; climate layers and soil landscapes of Canada).



(Knight, 2017)

Statistical Analysis

Very little is known about Common Nighthawk habitat associations in the boreal forest; to determine the most important covariates we used an exploratory boosted regression tree (BRT) modelling approach. A BRT model uses machine learning to maximize the predictive performance of the model by combining regression trees with boosting (Elith et al. 2008). The regression trees fit the explanatory variables to the response variable by recursively splitting the data into homogenous rectangular groups and fitting a constant for each explanatory variable to each group (De'Ath & Fabricius 2000). Regression trees are well suited for modelling complex ecological data because they are insensitive to covariance, outliers, and missing values while considering complex interactions between any data type (e.g., numerical or categorical). The boosting improves the predictive performance of the regression trees by iteratively fitting regression trees in a forward stagewise process to reduce deviance (Elith et al. 2008).

Prior to habitat modelling, we checked for sampling bias in our sampling design by comparing ARU stations to 1000 random locations within the study area. We conducted this comparison because the archived acoustic data used to build our dataset was collected across six different projects, each with different objectives. Therefore, we may not have adequately sampled the range of environmental variables in our study area. To ensure adequate sampling, we plotted the distribution of each continuous environmental variable at random locations and ARU stations using violin plots and checked for any variables that did not overlap. We assessed sampling

bias of our only categorical variable, natural subregion, by assessing the map coverage within our study area (Figure 1).

We built two BRT models to address the complex life history and spatial use of Common Nighthawks. The first model was a home range selection model that used presence or absence of Common Nighthawk detection as the response variable with a binomial distribution. The second model was a territory selection model that used the presence or absence of Common Nighthawk wing-boom as the response variable with a binomial distribution. Male Common Nighthawks defend a small territory for mating and nesting with aerial displays and frequent vocalizations (Brigham et al. 2011), but individuals can also vocalize while travelling to foraging or roosting sites forage several kilometres from the territory. Therefore, Common Nighthawk presence is likely indicative of home range selection, but vocalization rate may be a more informative proxy for habitat types that are important for Common Nighthawk breeding sites.

We accounted for detectability and differences in effort between ARU stations by including a summed detectability variable as an offset in all models. First, we calculated a detectability parameter by using Akaike information criterion (AIC; Burnham & Anderson 2003) to select the most parsimonious parametric survival model that accounted for differences in recording day of year and time of day. The detectability parameter calculation selected was:

$$p = 1 - e^{a_i + b_i + d(a_i \times b_i)}$$

where a is the negative of the duration of the recording,

and b is a statistic from the survival model that includes time of day and day of year, and d indicates the interaction between the two terms. We then calculated the detectability parameter of each recording, summed the detectability parameters at each survey location, and scaled the results from 0 to 1 to produce an effort offset that accounted for differences in the number of recordings and recording schedule across ARU stations.

To determine the optimal settings for the BRTs, we examined all possible combinations of a range of learning rates and tree complexity values for each of the two BRTs following Elith et al. (2008). The learning rate determines how much each successive tree contributes to the overall growing model, while tree complexity controls the depth of interactions between explanatory variables. We selected the combination of learning rate and tree complexity with the lowest residual deviance and at least 1,000 trees. We used a bag fraction of 0.75 for all models. The number of trees was determined by the lowest residual deviance across ten cross-validation folds. We also used 10-fold cross validation to assess the predictive performance of each BRT, using the predictive deviance relative to initial deviance to assess variation explained, the receiver operating characteristic (ROC) area under the curve (AUC) to assess model fit, and the difference between the training ROC AUC and the cross-validation ROC AUC to check for overfitting (Elith et al. 2008). We plotted the nine environmental variables with the highest relative influence for each model to examine the direction of the strongest explanatory variables. We interrogated pairwise interactions between environmental variables and reported any interactions with a multiplicative strength



greater than 2.

Finally, we tested for a difference in explanatory power between spatial scales with paired Wilcoxon signed-rank tests for each BRT, including only those variables that were sampled at both scales. We scaled the relative influence of the 25 variables that were common between scales and model type by computing the sum of the relative influence of these variables (i.e., we removed the relative influence of those variables that only existed at only one scale). We conducted four paired Wilcoxon signed-rank tests. The first two tests compared the relative influence of 300 m scale variables to 3 km variables for each of the habitat selection models (home range and territory) to determine which scale explained the most variation for each of the models. The second two tests compared the relative influence of the variables within the home range selection model to those in the territory selection model for each of the two variable scales (300 m and 3 km), to determine whether either scale was more important for a particular order of selection.

Environmental variable extraction was done in Geospatial Modelling Environment (Beyer 2014) and ArcGIS 10.3 (ESRI 2012). Statistical analyses was conducted in R version 3.3.1 (R Core Team 2016), with the dismo library h (Hijmans et al. 2017).

Results

Sampling Bias

We found minimal evidence of a bias in environmental variable sampling when we pooled the ARU stations across the six archived bioacoustic projects (Figure 2). None of the 55 continuous variables we considered had overlap in their sampling distribution. The archived bioacoustic dataset was somewhat biased in that it did not sample the upper ranges of the proportion of road within a 300 m and 3 km radius. There was also a sampling bias within the archived bioacoustic datasets across the natural subregions in the study area (Figure 1). The majority (92.4%) of the 1,082 ARU stations were located in the central mixedwood subregion, although the central mixedwood was the dominant natural subregion in the study area. The remaining ARU stations were in the Athabasca plain subregion (5.8%), the lower boreal highlands (1.1%), and the dry mixedwood (0.7%). There were no samples collected within the upper boreal highlands or the kazan uplands, although the latter natural subregion comprised a small proportion of the study area.



(Knight, 2017)

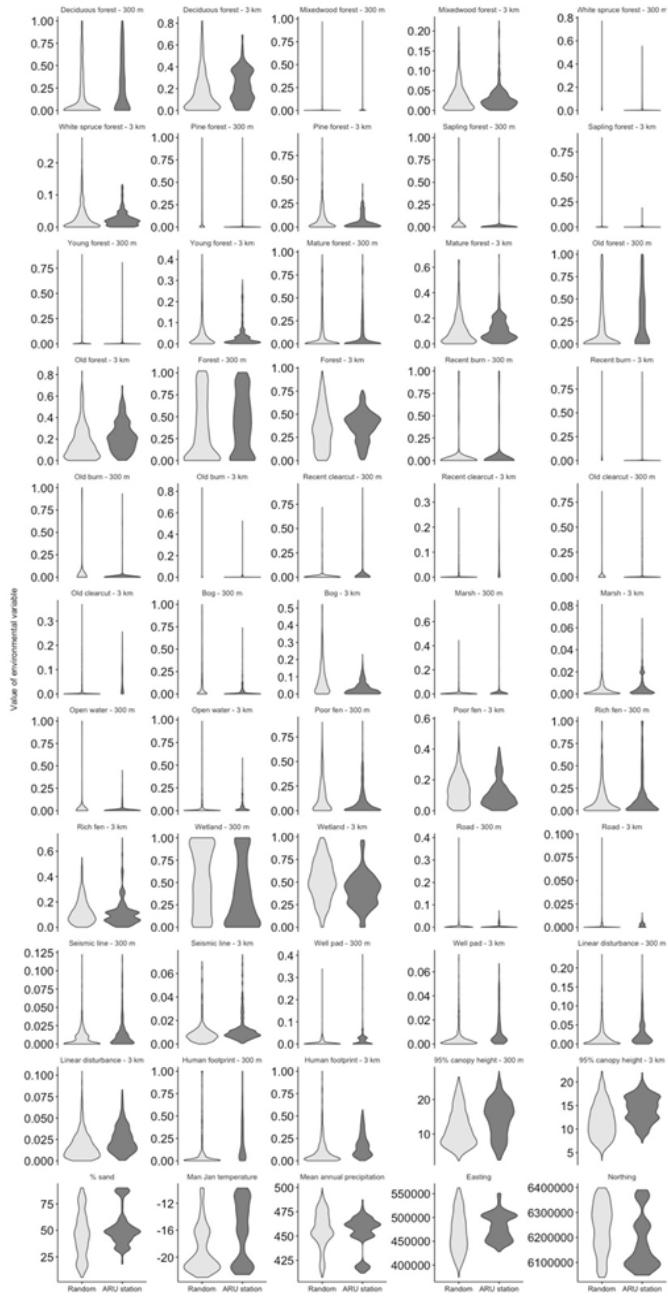


Figure 2. Distribution of environmental variables extracted for Common Nighthawk modelling at random locations within the study area and at sampled ARU stations. Most variables were measured as proportion within a radius of the scale described in the label. Mean January temperature (degrees Celsius), mean annual precipitation (mm), and % sand were measured as the mean value within a 3 km radius. Northing and easting are point values in NAD 83 UTM zone 12 N.

Home Range Selection

Common Nighthawks were detected at 388 of the 1,082 ARU stations surveyed. At ARU stations where Common Nighthawks were detected, the mean number of vocalizations detected was between 1 and 5,174, with a mean of 252 ($SD=637$). After correcting for recording effort and detectability, the number of vocalizations detected per recording was between 0.01 and 52.66, with a mean of 2.63 ($SD=6.57$).

We used a learning rate of 0.01 and a tree complexity of 5 to minimize the predictive deviance of the habitat selection model (Table 1). The global model had 3,100 trees, with a total mean deviance of 1.30 and cross validation predictive deviance of 0.68 ($se=0.03$), meaning that the global model explained 48% ($se=3\%$) of the variation in the data. The ROC AUC was 0.99 in training and 0.92 ($se=0.01$) in 10-fold cross-validation, suggesting excellent prediction and moderate but not excessive overfitting. The cross-validation correlation was 0.75, also suggesting good prediction.

The location of the ARU station had a strong influence on Common Nighthawk home range selection, with northing as the strongest predictor (relative influence 18.48), easting as the fourth strongest predictor (relative influence 4.33; Table 2, Figure 3), and home range selection strongest in the northwest of the study area. Climate also had a strong influence with a greater marginal effect on home range selection at ARU stations with lower mean January temperature (C° ; relative influence = 17.62). The proportion of pine forest within 3 km was the third strongest predictor (relative influence 5.66), with a negative marginal effect on habitat suitability at



stations with less than approximately 30% pine within a 3 km radius. Wetland variables, particularly the proportion of rich fen, bog, and poor fen all had influence on territory selection, with the marginal effect on home range selection 0 or negative, except for at ARU stations with less than 10% rich fen or 0% bog in the surrounding 3 km. There were strong interactions between all the top-ranked predictors, particularly mean January temperature and northing, which could explain the high relative influence of these two variables (Table 3).

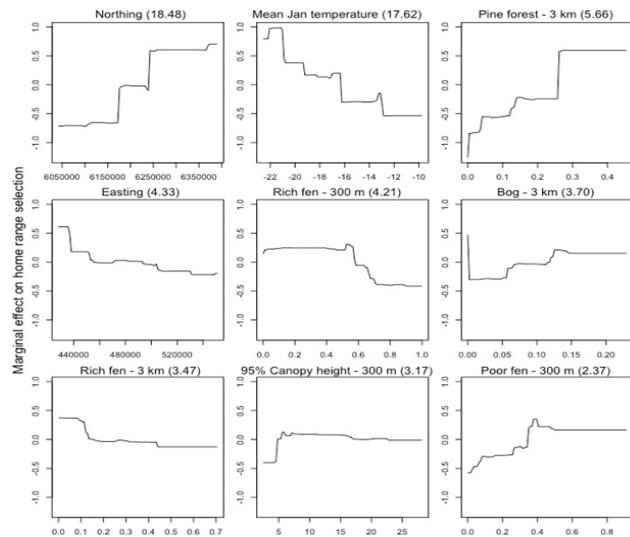


Figure 3. Environmental predictors of home range selection in a boosted regression tree (BRT) model. The top nine of 56 predictors are shown, as ranked by relative influence in the model (shown in parentheses). Variables are measured as proportion within a radius of the scale described in the label. Mean January temperature is the mean value within a 3 km radius and is measured in degrees Celsius. Northing and easting are point values in NAD 83 UTM zone 12 N. Y axes are on the logit scale and are centered to have zero mean over the data distribution.

Territory Selection

Common Nighthawk wingbooms were detected at 154 of the 1,082 ARU stations surveyed. At ARU stations where Common Nighthawk wingbooms were detected, the mean number of wingbooms detected was between 1 and 210, with a mean of 22.64 ($SD=38.90$). After correction for recording effort and detectability, the number of vocalizations detected per recording was between 0.003 and 2.97, with a mean of 0.25 ($SD=0.46$).

We used a learning rate of 0.005 and a tree complexity of 2 to minimize the predictive deviance of the habitat selection models (Table 1). The performance of the territory selection model was similar to the home range selection model. The global model had 1,700 trees, with a total mean deviance of 0.82 and cross validation predictive deviance of 0.044 ($se=0.02$), meaning that the global model explained 46% ($se=3\%$) of the variation in the data. The ROC AUC was 0.99 in training and 0.93 ($se=0.01$) in 10-fold cross validation. The cross-validation correlation was 0.69.

Climate variables had a strong influence on Common Nighthawk territory selection as well, with mean annual precipitation as the strongest predictor (relative influence 18.88), a combined relative influence of 25.30 (Table 2, Figure 4). Common Nighthawk territory selection was high at low mean January temperatures and ARU stations with low mean annual precipitation, then dropped sharply to no marginal effect above -20°C and 420 mm precipitation. The proportion of seismic lines had a strong positive effect on Common Nighthawk territory selection (relative influence = 10.47), with a positive marginal effect at ARU stations with more than 7% seismic lines.

in the surrounding 300 m. Wetland variables, including poor fen and total wetland within 3 km were also important, with high territory selection at ARU stations with minimal wetland, dropping sharply to no marginal effect with any wetland on the landscape. Upland variables, including deciduous forest, pine forest, and mixedwood forest were also important, with a strong positive marginal effect at ARU stations that were completely deciduous within a 300 m radius and a negative marginal effect at ARU stations with less than 5% mixedwood forest within 3 km. Similar to home range selection, there was a negative marginal effect on territory selection at ARU stations with less than 30% pine in the surrounding 3 km. Territory selection varied across the natural subregions (relative influence 4.64), with a positive marginal effect in the lower boreal highlands, and dry mixedwood, and a negative marginal effect in the central mixedwood and Athabasca plain. There were less interactions in the territory selection model, most of which did not include the strongest predictors in the model (Table 3). Of the top predictors in the model, the proportion of seismic lines had interactions with several other strong predictors including mean annual precipitation (16.81) and natural subregion (3.10).

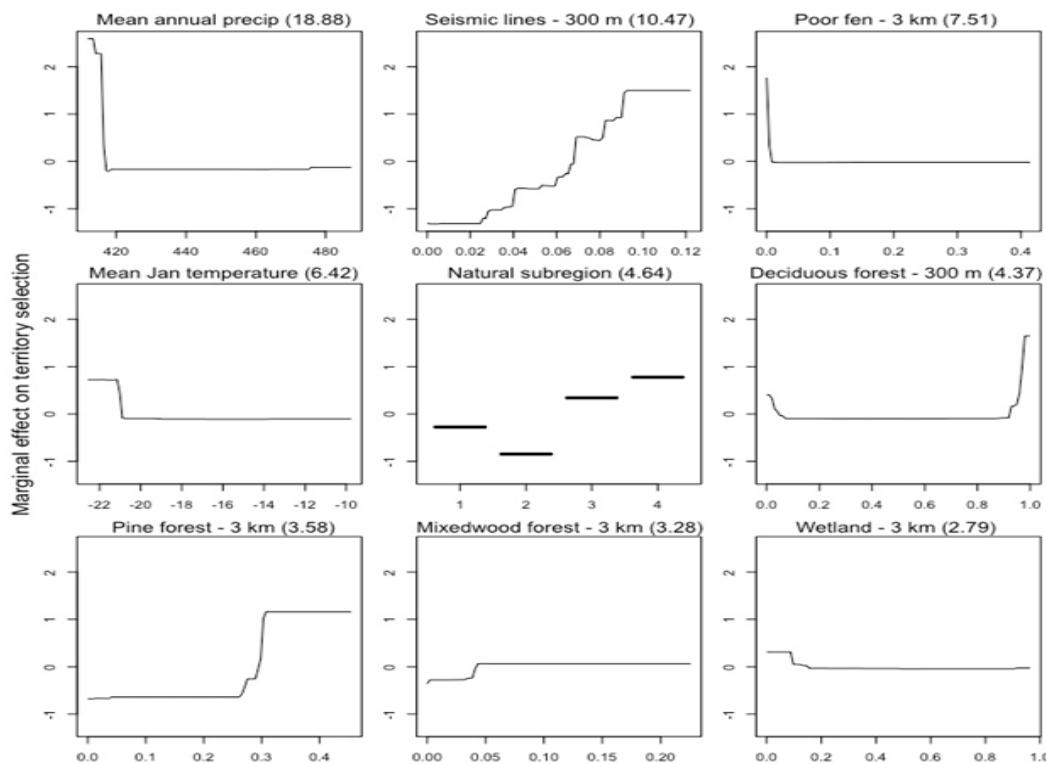


Figure 4. Environmental predictors of Common Nighthawk territory selection in a boosted regression tree (BRT) model. The top nine of 56 predictors are shown, as ranked by relative influence in the model (shown in parentheses). Variables are measured as proportion within a radius of the scale described in the label. Mean January temperature (degrees Celsius) and mean annual precipitation are measured as the mean value within a 3 km radius. Natural subregion is a point value and are coded as 1 = Athabasca Plain, 2 = Central Mixedwood, 3 = Dry Mixedwood, 4 = Lower Boreal Highlands. Y axes are on the logit scale and are centered to have zero mean over the data distribution.

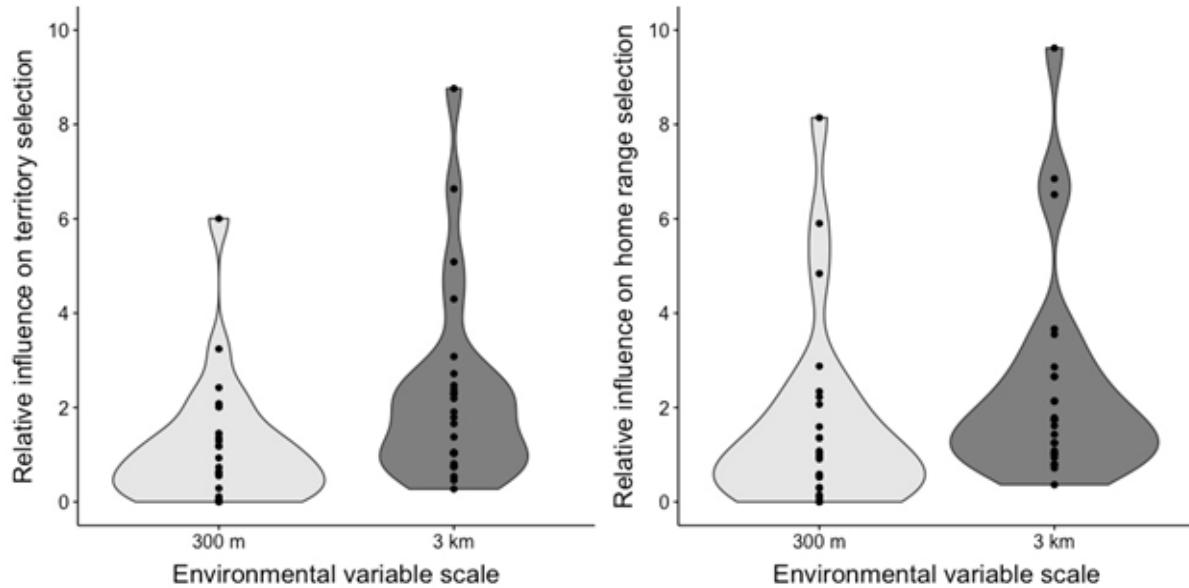


Figure 5. Relative influence of environmental variables measured at the local scale (300 m radius) and landscape scale (3 km radius) on Common Nighthawk home range selection and territory selection.

Influence of Scale

There were 25 environmental variables in each model that were measured at the 300 m and 3 km scale (Table 1). Contrary to our hypothesis, environmental variables measured at the 3 km scale had a greater relative influence on habitat selection than environmental variables measured at the 300 m scale in both the home range and territory selection BRT models ($V=0, P < 0.001; V=65, P = 0.007$ respectively; Figure 5). There were no differences in relative influence between the home range selection and the territory selection models for either the 300 m or the 3 km scale variables ($V=163, P = 0.72; V=191, P = 0.46$). For the home range selection model, the total relative influence of the 3 km scale variables was 60.17 and the total relative influence of the 300 m scale variables was 39.83. For the territory selection model, the total relative influence of the 3 km scale variables was 56.65 and the total relative influence of the 300 m scale variables was 43.35.

Discussion

The rise of bioacoustic technology has created large archived datasets of acoustic recordings that have the potential to fill baseline data gaps for understudied species that communicate acoustically. We used six archived bioacoustic projects and automated signal recognition software to build a baseline dataset for Common Nighthawks in the boreal forest. Our resultant dataset had an order of magnitude of more detections than previously existing datasets (Hache et al. 2014). We used this new baseline dataset to model Common Nighthawk habitat selection in the boreal forest for the first time and examined the influence of scale on home range and territory selection. Using an archived dataset

for new objectives can lead to sampling bias; however, we found minimal sampling bias in the environmental variables included in our analysis except for our sampling of natural subregion; therefore, caution should be used when extrapolating the results of our study to natural subregions in Alberta other than the central mixedwood. Further sampling is needed to fill in some gaps in coverage of certain covariates as well.

Common Nighthawk home range selection and territory selection were related to different environmental variables, as expected given that Common Nighthawks defend small territories where they are highly active, but can forage far from the territory within large home ranges (Ng 2009). Even songbird species, which are traditionally thought to fulfill their life history within their territory boundaries (Nice 1941), can use areas outside their territory with differing habitat associations. For example, endangered Golden-Winged Warblers use mature forested areas for perching and foraging outside their early-successional forest territories (*Vermivora chrysopera*; Streby et al. 2012) and Wood Thrush roost in denser vegetation than their defended territory (*Hylocichla mustelina*; Jirinec et al. 2016). Examining habitat selection at multiple hierarchical scales is important for identifying the habitat characteristics associated with limiting parts of a species' life history because the characteristics selected for at the second-order scale (Johnson 1980) are often different from the characteristics selected for at the third-order scale (Mayor et al. 2009). The strong relative influence of broad geographic and climatic variables at the second-order scale demonstrated here suggest that third-order selection is particularly important for highly-mobile species with large home ranges like the Common

Nighthawk that may not have strong selection for more specific landcover types at the second-order scale. All previous habitat studies for Common Nighthawks have been at the second-order or nest microhabitat scale. One recent study in Ontario's boreal forest used a second-order occupancy modelling framework (MacKenzie et al. 2002) and found no difference in habitat association between forest types or between open wetlands, clearcuts, and burns; perhaps because Common Nighthawks in that region only select for those environmental features at third-order scales.

Except for the recent study by Farell et al. (2017), all previous regional Common Nighthawk habitat selection studies have been restricted to the southern areas of the range (New Mexico: Pidgeon et al. 2001; south Saskatchewan: Ng 2009; southeast Wisconsin: Viel 2014; USA shortgrass prairie: McLachlan) making comparison between habitat associations difficult. One contrast of our results that stands out is that Common Nighthawks did not select for or negatively selected for various types of wetlands both at the home range and the territory scale. Ng (2009) has previously shown that Common Nighthawks are more abundant at grassland sites that are close to waterbodies and Common Nighthawks are known to forage over waterbodies for emergent aerial insects in southern areas (Brigham et al. 2011). In the boreal forest, Common Nighthawks may not be associated with wetland and aquatic areas because insect availability is not restricted to waterbodies and diet sample analysis suggests Common Nighthawks are not reliant on insects of aquatic origin (Knight et al. in review b). Alternatively, we may have found a negative relationship between waterbodies and Common Nighthawks because



(Noble, 2017)

Common Nighthawks may be silent during foraging and the data collection method we used relies on acoustic detections. Brigham et al. (2011) have stated in the Birds of North America account that "Nighthawks seem to exploit water sources for abundant insects and it is important to learn the degree of this dependency" and our results suggest that this dependency may not extend to the boreal biome. Habitat selection studies in other areas of the boreal forest should further explore a potential dependency on waterbodies for foraging.

Some of the strong predictors of territory selection found here can be related to Common Nighthawk nest-site characteristic studies, which have unanimously found that nests are located in areas of bare ground (Lohnes 2010; Hausleitner & Wallace 2012; Allen & Peters 2012; Jennifer 2015). We found that mean annual precipitation (MAP) was the strongest predictor of territory selection, likely because lower precipitation causes lower primary productivity and thus more open areas for nesting sites. Common Nighthawks may also be associated with areas of lower precipitation because they lay their eggs on bare ground, and higher precipitation could create a higher risk of nest failure (Fisher et al. 2015). We also found Common Nighthawk territory selection to be strongly

associated with seismic lines, which may also provide open areas for nesting sites. Haché et al (2014) have also previously found a positive relationship between Common Nighthawk presence and anthropogenic disturbances. Contrary to known habitat associations from natural history observations (Brigham et al. 2011), we did not find that Common Nighthawks selected for recent burns or clearcuts. Farrell et al. (2017) have previously shown that burns and clearcuts provide habitat for Common Nighthawks. We may not have found a strong selection for post-burn and post-clearcut areas because the remotely sensed dataset that we extracted our environmental variables from classified recent burns and clearcuts as within 20 years of the disturbance, which may be longer than burns and clearcuts provide suitable habitat for Common Nighthawks. Further, there may be interactions with vegetation type that might mediate post-disturbance regeneration and thereby habitat suitability. Future research should explore Common Nighthawk habitat selection along a post-disturbance temporal gradient in further detail.

Regardless of the specific variable, smaller-scale environmental variables have been shown to explain bird habitat associations during the breeding season better than larger-scale variables (Hostetler & Holling 2000); however, we found that the landscape scale (3 km) variables were stronger predictors of Common Nighthawk habitat selection. Landscape scale variables explained more variation for both the home range selection and territory selection model, which was contrary to our prediction that landscape scale variables would better explain home range selection and local scale variables

would better explain the territory selection model. Fisher and Volpe (2011) showed that mammals body size is related to scale of habitat selection; however, Mayor et al. (2009) suggest that the scale at which animals perceive and interact with their environment may in fact be a better predictor. In that case, a highly-mobile aerial species like the Common Nighthawk would be expected select habitat at large scales, regardless of the order of habitat selection. Previous habitat selection studies have used smaller scales than our study (400 m and 800 m: Ng 2009; 500 m: Viel 2014; 400 m: Farrell et al. 2017). We suggest that future work should include larger scales and examine a range of scales to determine the dominant scale of Common Nighthawk habitat selection (Holland et al. 2004).

The success of our Common Nighthawk case study highlights the potential value of archived bioacoustic datasets. Luther and Derryberry (2012) have used archived bioacoustic recordings to study change in bird community over time; however, we know of no other studies that have used archived recordings to fill a baseline data gap. As bioacoustic technology continues to develop and use continues to increase, the archived datasets available for such research will continue to grow. We suggest practitioners that are developing such bioacoustic datasets to include dusk and nocturnal sampling in their recording schedules to facilitate future use of the dataset for other species, including understudied crepuscular species like the Common Nighthawk and other nightjar species. We encourage the use of these growing bioacoustic datasets for monitoring and research of understudied species and species of conservation concern if minimal sampling bias is appropriately confirmed prior to use.



(Knight, 2017)

Conservation Implications

The proportion of ARU stations at which we detected Common Nighthawks suggests that this species is more common in the boreal forest than previously thought. Large-scale habitat modelling by Haché et al. (2014) also suggests the boreal forest in Alberta supports high densities of Common Nighthawks. Conservation of healthy Common Nighthawk populations in the boreal forest may be important for conservation of the species, especially given the almost 80% decline shown in southern areas (Environment Canada 2016). Land and wildlife managers should be aware of the potential presence of this federally Threatened species, particularly in areas with more than 30% pine forest and areas with a high density of seismic lines. Common Nighthawks nest later than most bird species and can have active nests through late August (Brigham et al. 2011), so land managers should also conduct due diligence to ensure Common Nighthawks nests are not disturbed by land clearing or construction activities, as per the Species at Risk Act and the Migratory Birds Convention Act. Appropriate surveys should be conducted to determine the presence of Common Nighthawks, as the order of magnitude increases in detections



from our one year ARU study relative to all previous detections, suggesting that dawn point count surveys are insufficient. Past studies have indicated Common Nighthawks often spend time adjacent to or even roosting on gravel roads. In areas dominated by pine forests where Common Nighthawks are more abundant, changing travel speeds on roads may be warranted if collisions with nighthawks become an issue.

Our study demonstrates that ARUs with a crepuscular component in the recording schedule can provide high detectability surveys for Common Nighthawks. Alberta survey guidelines are also available (Alberta Environment and Sustainable Resource Development 2013), or a Canadian citizen science roadside survey protocol (Knight et al. 2017). Existing protocols emphasize the importance of documenting wingbooms if the survey objective relates to nesting habitat, and our study supports this recommendation because we found Common nighthawk wingbooms were associated with different environmental variables than vocalizations. The difference between selected habitat variables of our home range selection model and our territory selection model also suggests that Common Nighthawk habitat selection and use is complex and multi-scaled. The present study provides an overview of habitat relationships, but more detailed habitat selection work is needed to understand the reliance of this species on specific habitat features, particularly on natural disturbances and human disturbed habitats. Future work should consider the difference in selection between different habitat components (Johnson 1980). Given the reliance of Common Nighthawk surveys on acoustic cues, due to the birds' crepuscular nature,

future work should also consider how varying acoustic signals can be related to habitat components.

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(Parayko, 2017)

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Tables

Table 1. Predictive deviance receiver operating characteristic area under the curve (AUC) of boosted regression tree (BRT) models across combinations of learning rates and tree complexity values explored to determine optimal settings for two BRT models. The home range selection model used presence or absence of Common Nighthawk call as the response variable and the territory selection model used presence or absence of Common Nighthawk wingboom as the response variable. Bold indicates the combination of learning rate and tree complexity values chosen for each model. All values presented were from 10-fold cross-validation.

Learning Rate	Tree Complexity	Home Range AUC	Home Range Deviance	Territory AUC	Territory Deviance
0.01	2	0.915	0.695	0.927	0.437
0.01	3	0.916	0.694	0.932	0.433
0.01	4	0.918	0.699	0.929	0.445
0.01	5	0.920	0.681	0.929	0.446
0.005	2	0.918	0.691	0.932	0.423
0.005	3	0.919	0.681	0.925	0.453
0.005	4	0.920	0.684	0.932	0.438
0.005	5	0.919	0.688	0.932	0.432
0.001	2	0.911	0.722	0.922	0.461
0.001	3	0.917	0.697	0.930	0.441
0.001	4	0.918	0.690	0.932	0.429
0.001	5	0.916	0.692	0.930	0.439
0.0005	2	0.902	0.773	0.922	0.485
0.0005	3	0.914	0.721	0.930	0.459
0.0005	4	0.916	0.712	0.929	0.444
0.0005	5	0.917	0.701	0.932	0.436
0.0001	2	0.878	0.940	0.891	0.613
0.0001	3	0.885	0.911	0.902	0.596
0.0001	4	0.892	0.888	0.909	0.587
0.0001	5	0.899	0.872	0.917	0.574

Multi-scale Selection of the Common Nighthawk

Table 2a. Relative influence of environmental variables included in two boosted regression tree (BRT) models of Common Nighthawk habitat selection: home range selection and territory selection. All variables were extracted at two scales (300 m and 3 km) except variables with a raster cell size greater than the territory scale radius or that covaried with a correlation coefficient > 0.9, which were extracted at the 3 km scale only. All variables were included in each of the two models. All environmental variables were measured at both territory (300 m) and home range (3 km) scales.

Variable	Calculation type	Source dataset	Home range selection (300 m)	Home range selection (3 km)	Territory selection (300 m)	Territory selection (3 km)
Deciduous forest	Proportion	Avian habitat classification	1.18	1.94	4.04	0.31
Mixedwood forest	Proportion	Avian habitat classification	0.15	0.66	0.03	2.89
White spruce forest	Proportion	Avian habitat classification	1.10	1.41	0.37	1.66
Jack pine forest	Proportion	Avian habitat classification	0.84	5.10	0.87	3.42
Sapling forest	Proportion	Avian habitat classification	0.00	0.19	0.00	0.69
Young forest	Proportion	Avian habitat classification	0.48	0.54	0.42	0.92
Mature forest	Proportion	Avian habitat classification	0.31	0.92	0.79	1.11
Old forest	Proportion	Avian habitat classification	0.71	0.38	0.39	0.18
Forest	Proportion	Avian habitat classification	0.16	0.50	0.42	0.71
Recent burn (< 20 yrs)	Proportion	Avian habitat classification	0.00	0.94	0.19	0.36
Old burn (> 20 yrs)	Proportion	Avian habitat classification	1.24	0.57	2.18	1.20
Recent clearcut (< 20 yrs)	Proportion	Avian habitat classification	0.28	0.86	0.79	0.50
Old clearcut (> 20 yrs)	Proportion	Avian habitat classification	0.08	0.42	0.07	0.69
Bog	Proportion	Avian habitat classification	0.51	3.45	1.63	1.83
Marsh	Proportion	Avian habitat classification	0.06	1.14	0.01	1.54
Open water	Proportion	Enhanced wetland classification	0.05	1.41	0.00	1.54
Poor fen	Proportion	Enhanced wetland classification	2.56	1.88	1.40	5.89
Rich fen	Proportion	Enhanced wetland classification	4.31	3.63	1.35	2.07
Wetland	Proportion	Enhanced wetland classification	0.57	0.42	0.49	4.46
Road	Proportion	Human footprint index	0.28	0.66	0.03	1.60
Seismic line	Proportion	Human footprint index	1.52	1.52	10.74	1.47
Well pad	Proportion	Human footprint index	0.72	0.92	0.63	1.28
Linear disturbance	Proportion	Human footprint index	0.30	0.54	0.41	0.50
Human footprint	Proportion	Human footprint index	0.55	0.76	0.91	0.54
95% canopy height	Mean	Forest structure index	3.13	1.13	0.98	0.70



Table 2b. Relative influence of environmental variables included in two boosted regression tree (BRT) models of Common Nighthawk habitat selection: home range selection and territory selection. All variables were extracted at two scales (300 m and 3 km) except variables with a raster cell size greater than the territory scale radius or that covaried with a correlation coefficient > 0.9, which were extracted at the 3 km scale only. All variables were included in each of the two models. All environmental variables were measured at home range (3 km) scale only or no scale.

Variable	Calculation type	Source dataset	Home range selection (3 km)	Territory selection (3 km)
% Sand	Mean	Soil landscapes of Canada	1.33	1.55
Mean January temperature	Mean	Climate surface	19.23	4.86
Mean annual precipitation	Mean	Climate surface	0.89	18.48
Natural subregion	Point value (no scale)	Avian habitat classification	3.87	3.93
Easting	Point value (no scale)	Natural subregions	3.53	1.98
Northing	Point value (no scale)	Avian habitat classification	18.18	2.01

Table 3. Pairwise interactions between environmental variables in two boosted regression tree (BRT) models of Common Nighthawk habitat selection: home range selection and territory selection. Interaction strength is reported as multiplicative strength, and only interactions with multiplicative strength greater than 2 are reported here.

Variable 1	Variable 2	Interaction strength
Home range selection model		
Mean January temperature	Rich fen – 300 m	9.47
Northing	Pine forest – 3 km	8.86
Northing	Rich fen – 300 m	8.26
Mean January temperature	Bog – 3 km	7.73
Northing	95% canopy height – 300 m	7.46
Easting	% sand	6.52
Northing	Easting	5.84
Mean January temperature	Pine forest – 3 km	3.99
Mean January temperature	Natural subregion	3.53
Mean January temperature	% sand	3.34
Mean January temperature	95% canopy height – 300 m	2.84
Northing	Bog – 3 km	2.76
Easting	Deciduous forest – 3 km	2.68
Northing	Rich fen – 3 km	2.65
Bog – 3 km	Deciduous forest – 3 km	2.23
Easting	White spruce forest – 3 km	2.08
Territory selection model		
Mean annual precipitation	Seismic line – 300 m	16.81
95% canopy height – 3 km	Recent clearcut – 300 m	13.26
95% canopy height – 300 m	Recent clearcut – 300 m	5.01
Well pad – 3 km	Seismic line – 300 m	4.82
Mixedwood forest – 3 km	Deciduous forest – 300 m	4.01
Bog – 300 m	Seismic line – 3 km	3.15
Natural subregion	Seismic line – 300 m	3.1
Bog – 300 m	Pine forest – 300 m	2.39



Appendix

Appendix 1. Details of archived bioacoustic projects used to collect Common Nighthawk baseline data.

Project	Focus	Data proprietor	Minutes of data collected/day	Recording schedule	Mean # days deployed
Big grid	Intensive sample for biodiversity in large arrays of ARUS in areas of oil and gas development	Bioacoustic Unit	240	10 minutes on every hour	23
Old growth	ARU sampling in old growth upland habitat	Bioacoustic Unit/ Environment and Climate Change Canada	240	10 minutes on every hour	7
Road	Paired on-road and off-road sampling on roadside survey transects	Bioacoustic Unit	480	10 minutes on every hour plus 10 minutes on, 10 minutes off between dusk and dawn	2
Songbird triangulation	ARU sampling on regenerating well pads	Bioacoustic Unit	240	10 minutes on every hour	3
Understory protection	ARU sampling in cutblocks, intact forest, and understory retention sites	Bioacoustic Unit	240	10 minutes on every hour	8
Yellow Rail	Yellow Rail monitoring in graminoid fens	Bioacoustic Unit	240	10 minutes on every hour	13

Appendix 2. Source geospatial datasets used to extract environmental variables for Common Nighthawk habitat modelling.

Name	Proprietor	Original data format (cell size)	Variables extracted	Available from (access date)	Available reference or metadata
Avian habitat classification	Environment and Climate Change Canada	Raster (30 m)	Upland forest classes	Proprietary – not available	Martin-Demoor & Mahon 2014
Enhanced wetland classification	Ducks Unlimited	Raster (30 m)	Wetland classes	Proprietary – not available	Ducks Unlimited Canada 201
Human footprint index	Alberta Biodiversity Monitoring Institute	Polygon		http://www.abmi.ca/home/data-analytics/da-top/da-product-overview/GIS-Human-Footprint-Land-Cover-Data/HF-inventory.html (05-01-2017)	Alberta Biodiversity Monitoring Institute 2014
Forest structure index	University of British Columbia	Raster (30 m)	95% canopy height	Proprietary – not available	Coops et al. 201
Climate layers	Alberta Biodiversity Monitoring Institute	Raster (500 m)	Mean January temperature, mean annual precipitation	Proprietary – not available	Hamann et al. 2013
Soil landscapes of Canada		Raster (1000 m)	% sand	http://sis.agr.gc.ca/cansis/nsdb/slcl/v3.2/index.html (05-01-2017)	Schut et al. 201
Natural subregions	Alberta Parks and Environment	Polygon	Natural subregion	https://www.albertaparks.ca/albertaparksca/management-land-use/alberta-conservation-information-management-system-acims/download-data/ (05-01-2017)	Natural Regions Committee 2006