Ovenbird response to vegetation regeneration and conspecific density at reclaimed oil and gas wells in the boreal forest of Alberta.

INTRODUCTION

Monitoring programs and research studies increasingly rely on recording technology to survey birds (Blumstein et al. 2011, Shonfield and Bayne 2017). Due to challenges in estimation of area sampled, and difficulty with accurate determination of individuals, standard bioacoustic surveys can lack the resolution to determine fine scale associations between birds and their habitat (Bayne et al. 2016, Darras et al. 2016, Yip et al. 2017). Despite this, recording technology has the potential to collect diverse types of data beyond point assessments (Dawson and Efford 2009, Blumstein et al. 2011, Shonfield and Bayne 2017). Arrays of microphones can be used to collect spatial data on birds through estimation of singing locations, based on their time of arrival difference to time synchronized microphones, termed localization (Blumstein et al. 2011). Combined with improving methodology on automated species and individual recognition from recording data, potential exists to track individuals through time, and determine fine scale habitat associations (Blumstein et al. 2011, Mennill et al. 2011, Shonfield and Bayne 2017).

Individuals can be tracked through time using acoustic data given that songs are individually distinctive, based on characteristics that do not degrade over time (Mennill 2011). Various classification methods are used to distinguish individuals based on song, which vary in time to perform, accuracy, and computational power required (Kirschel et al. 2011, Ehnes and Foote 2015). For species which display high variation in song between individuals, relatively simple and time efficient methods, such as spectrogram cross correlation (SPCC), continue to be valid approaches for individual identification despite advances in automated species recognition (Foote at al. 2012, Cramer 2013, Petrusková et al. 2016).

Challenges exist with collection of localization data using large arrays, including equipment requirements, and time to collect and process data. Calibrating the recording array based on species of interest, and habitat type is necessary for accurate spatial locations (Wilson et al. 2013). Although there is a move towards the use of sensor networks when using microphone arrays to monitor birds, localization has been performed successfully using commercially available equipment, and open source software (Mennill et al. 2012, Wilson et al. 2013). Various taxa, including marine mammals (Watkins and Schevill 1972, Hayes et al. 2000), primates (Spillmann et al. 2015), amphibians (Jones and Ratnam 2009), and songbirds (Kirschel et al. 2011) have been successfully monitored using localization. Most bird research studies have focused on validation of the method, and examination of the singing behaviour (Mennill et al. 2006, Fitzsimmons et al. 2008). Few studies have used localization to understand habitat associations, or response to human disturbance in birds.

There is growing need to collect fine scale data on bird communities, to accurately understand their response to different types of habitat change and human disturbance (Bayne et al. 2016). This is especially true in regions with rapid development, such as the boreal forest of Northern Alberta (Bayne et al. 2016). Populations of many songbird species in the boreal are declining and concerns have been raised that extensive oil and gas development may be partially responsible (Van Wilgenburg 2013). Among the disturbances created by the energy sector, are hundreds of thousands of one hectare, oil and gas well sites. Well sites no longer in production have been actively reclaimed in Alberta since 1963 using various criteria to define recovered. Previous emphasis has been placed on recovery of soil and vegetation attributes under the premise that other ecosystem components (i.e. animals) will begin to use recovered areas if habitat has been created (Cristescu et al. 2012, Jones and Davidson 2016).

However, other valued ecosystem components such as birds, do not always recolonize reclaimed features in a predictable relationship to soil and vegetation parameters (Cristescu et al. 2012). Increasing focus is placed on ecological function, including animal foraging and behaviour, to determine restoration success, and ensure long term recovery (Jones and Davidson 2016). Accounting for individual behaviour in response to disturbance has been assessed infrequently, and could improve accuracy of restoration assessments (Jones and Davidson 2016).

Few studies have attempted a combined approach of localization with individual identification, despite potential to do so (Kirschel et al. 2011). Our first objective was to track ovenbirds (*Seiurus aurocapilla*) using an acoustic location system, and recording data from omnidirectional microphones to identify individuals. The arrays used in this study was large to encompass the territories of multiple ovenbirds, which were not identified prior to collection of recording data. We hypothesized ovenbirds would be an excellent candidate to study using an acoustic location system to track their behaviour through time, based on their singing behaviour (Mennill 2011). Ovenbirds display large individual variation in song, and have previously been distinguished using SPCC (Ehnes and Foote 2015). Ovenbirds sing from the lower canopy, limiting error in localization compared to species which sing from the upper canopy.

The second objective was to apply the use of an acoustic location system to understand how ovenbirds respond to well site reclamation efforts. Ovenbirds are used as an indicator of recovery following forestry, and oil and gas disturbances in the western boreal forest (Bayne et al. 2005, Machtans 2006, Lankau et al. 2013). We hypothesized that ovenbird use of well sites, measured by singing locations on the well sites, should increase with canopy cover due to decreased probability of predation (Lankau et al. 2013). Ovenbird singing locations indicate territorial behaviour, and positions within a well site footprint should indicate habitat quality (Bayne et al. 2005). Ovenbirds will avoid sites at early stages of woody plant regeneration, to limit predation risk, and lack of foraging opportunity due to absence of leaf litter (Lankau et al. 2013). Increasing conspecific density increases use of these features as a landmark for territory boundaries (Heap et al. 2012, Lankau et al. 2013). The response of ovenbirds to regeneration is previously untested, and use of indicator with know responses to boreal disturbances should be useful for determining success of current reclamation standards.

METHODS

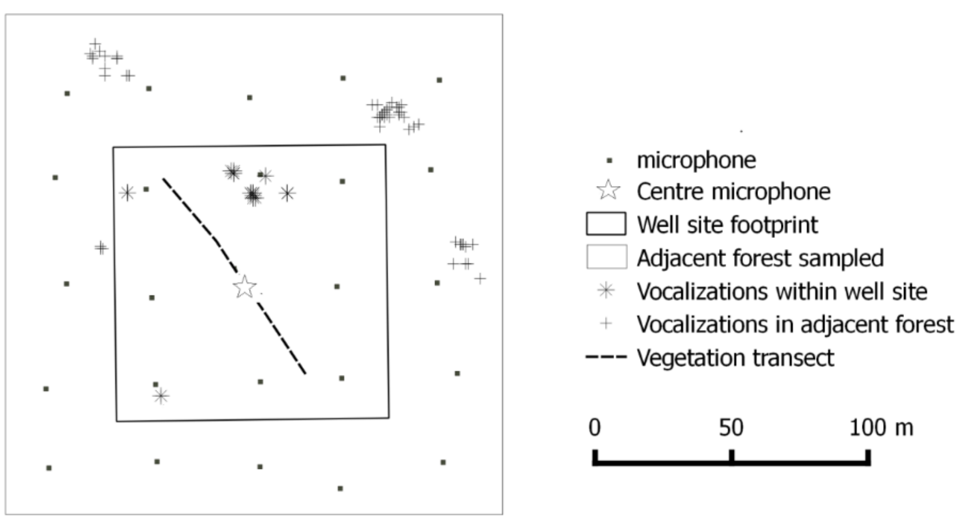

Figure 1. Schematic of study design. Ovenbird detections were measured within the well site, and area equivalent to the well site footprint in the adjacent forest.

SITE SELECTION

Certified reclaimed well sites (n=16) were selected within the central mixedwood sub region of the boreal forest natural region, within 50km of the communities of Lac La Biche, and Slave Lake, Alberta (Natural Regions Committee 2006). Sites were located in mesic upland ecosites where the main soil type was grey luvisols (Beckingham and Archibald 1996, Natural Regions Committee 2006). Adjacent forests were dominated by aspen poplar (*Populus tremuloides*), and balsam poplar (*Populus balsamifera*). Common understory shrubs included alder (*Alnus spp.*), willow (*Salix spp*.), and beaked hazelnut (*Corylus cornuta*).

Well sites ranged from 11 to 66 years since development, and 3 to 48 years since a reclamation certificate was issued. Reclamation treatments in forested lands have been updated multiple times since their initial implementation (Bott et al. 2016). For these reasons, sites were selected to sample a gradient of woody vegetation recovery, ranging from sites dominated by grass and forb cover, to sites with woody vegetation greater than five metres in height. Sites were required to be accessible by a linear feature, and have no significant additional human disturbance within the area sampled. Well site footprints covered an average of 1.01 ± 0.09 ha, determined through digitization of survey diagrams and ground truthing (Abadata 2016).

ACOUSTIC DATA COLLECTION

The acoustic location system used GPS enabled Wildlife Acoustic SM3 units equipped with external SMM-A1 microphones. A total of 400 microphones were deployed over the 16 sites during the bird breeding season (May-June) in 2015 and 2016. Microphones (n=25) were deployed to a height of 1.5m, and spaced an average of 33.9m ± 0.52m apart in a 5x5 grid. Arrays varied slightly in their design, covering an average area of 2.30 ± 0.25 ha. Positions were determined using a Hemisphere S320 survey GPS, set to a horizontal accuracy of ± 3.0cm. When not possible to obtain locations using the survey GPS due to dense canopy, positions were determined from the mounted Garmin 16x GPS attached to the recording unit (accuracy 3.28 ± 0.25m). Recordings were collected at each site from 5:30AM to 8:30AM on one day. Recordings were time synchronized to ±1 ms through the GPS clock of the Garmin 16x. A 48000 Hz sample rate was used, and recordings were collected in a compressed wac format.

It is necessary to quantify error in positional estimates using acoustic localization, as error will vary based on habitat type and species (Wilson et al. 2013). Playback experiments were performed at one of the study sites to quantify error in localization associated with the different spacing of microphones and GPS accuracy. The average baseline error in spatial locations was determined as 3.05± 0.39m, from n=576 singing events across n=14 passerine species. Error increased with inter-microphone distance, and accuracy of GPS, resulting in a maximum average error of 11.5 ± 0.91m.

VEGETATION DATA COLLECTION

The point intercept method was used along a 90m diagonal transect from randomly selected corner of the well site to the opposite corner (Figure 1). The maximum height of each species which intercepted the pole was recorded at each distance along the transect. Data from the point intercept method was summarized into percent canopy cover, which ranged from 0 to 100% at reclaimed wells.

ACOUSTIC DATA PROCESSING

Three hours of dawn chorus (5:30-8:30 AM) were selected for processing at each site. Recording files were converted to wave format and spectrograms were visualized using a 512 FFT hamming window in the program Audacity 2.1.3 (Audacity 2016). All files were grouped into four channel tracks based on spatial proximity, and scanned visually to locate ovenbirds performing territorial vocalizations within the microphone grid. Vocalizations were included in further analyses if the entire song was detected clearly on four microphones, and did not coincide with other songs of greater amplitude, or overlap with any fainter singing events for 25% of the duration of the target vocalization on any channel (Spiesberger 2001). The multichannel track which contained the strongest signal for each identified bird was used in subsequent analyses.

Hourly Environment Canada data were summarized from the weather station closest to each research site, and used for calculation of speed of sound (Wilson et al. 2013, E&CCC 2017). The multichannel tracks, microphone positions, and speed of sound, were imported into the MATLAB based program XBAT for analysis (Figueroa 2007, Math Works Inc. 2014). Each vocalization of that met criteria was annotated. The CSE location algorithm (version 2.3) was used for acoustic localization (Cortopassi 2006). This algorithm uses cross correlation of a selected signal between channels to determine the time of arrival difference of the signal to the microphone position associated with each channel of the recording (Cortopassi 2006**,** Campbell and Francis 2012). The time of arrival differences between channels are used to calculate the location of individuals based on the distance and bearing of the signal from the array under a known speed of sound (Cortopassi 2006). Each annotated vocalization was localized using a minimum of four channels using a search criteria of 100m (Campbell and Francis 2012).

Results were discarded if not closest to the channel with the greatest amplitude, however this occurred for few events, and often when obstructed by another vocalization. If singing locations did not occur within the multichannel track (resulting in positions outside the set of four microphones) but were still within the microphone grid, they were rerun in the correct multichannel track based on the estimated locations. This was to achieve the most accurate positions, as accuracy of localization degrades with distance from the centre of the array (Mcgregor et al. 1997, Campbell and Francis 2012, Wilson et al. 2013).

Singing locations were exported from and visualized in QGIS 2.12.3 (Quantum GIS Development Team 2016). A buffer the equivalent size of the well site polygon was created around each site in the adjacent forest (Figure 1). Vocalizations occurring beyond this buffer were excluded from subsequent analyses. Error in localization was accounted for by buffering well site footprints by error estimates based on GPS accuracy, and microphone spacing at different sites. If singing locations occurred within the buffer they were excluded from analyses as their position could not be confirmed as on, or off of the well site. Remaining singing locations were then classified as occurring within the well site footprint, or within the adjacent forest.

Each localized singing event was clipped from long recordings using the tuneR package on the recording of the microphone closest to the estimated position, adding a buffer of 0.25s on beginning and end of the song (Ligges 2016). We assigned vocalizations to individuals using hypothesis based on spatial locations, length of song, frequency range of song, and song timing. Hypothesized individuals with <10 singing locations were removed from further analysis. SPCC was performed in the program Raven Pro 1.5 to create a correlation matrix of pairwise comparisons of the vocalizations (Bioacoustics Research Program 2014). A 512 Hamming window spectrogram and bandpass filter of 1500Hz to 10500Hz was used for all processing. SPCC determines the similarity between two spectrograms, through shifting across time to find the point in time where amplitude is most similar between spectrograms (Terry et al. 2001, Cramer 2013).

STATISTICAL ANALYSES
The 95% confidence interval of the SPCC score from pairwise comparisons was calculated for each hypothesized individual, and an equal number of randomly selected pairwise comparisons with other hypothesized individuals. If confidence intervals of SPCC score within and between individuals were not overlapping, vocalizations were assigned to these individuals for further analysis. The number of conspecifics was calculated for each site based on these estimates.

A mixed effects logistic regression was used to determine how canopy cover, and number of conspecifics at the site influenced placement of singing locations within the well site footprint (1) or within the adjacent forest (0) (R package 'lme4', Bates 2015). The hypothesized individual was included as a random effect to account for repeated observations. The conditional, and marginal r^2 was calculated using the R package MuMin (R package 'MuMIn', Barton 2016).

RESULTS
A total of 1375 ovenbird vocalizations were detected across the 16 well sites. After removing hypothesized individuals with <10 vocalizations, and vocalizations obstructed by masking, 509 occurred within well site footprints, and 866 occurred in the adjacent sampled area. The average correlation score from SPCC within individuals was 0.448 ± 0.01, and 0.225 ± 0.01 between individuals (Figure 2). The data suggested 22 distinct individuals, which demonstrated non-overlapping confidence intervals of correlations between themselves, and other birds. As canopy cover increased, probability that ovenbirds would sing from well sites increased (Table 2). As conspecific density near the well site increased, ovenbirds were less likely to sing from the well site (Table 2).

Figure 2. Bar chart of mean correlation scores from SPCC within individuals, and between individuals. Error bars indicate the mean + 95% confidence interval.

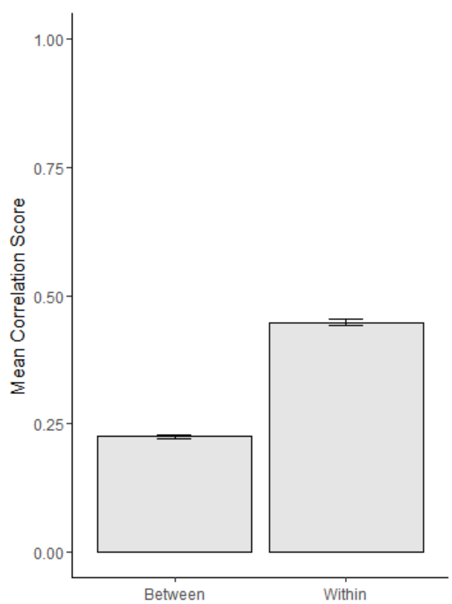

Table 1. Results from logistic regression (conditional r^2=0.328, marginal r^2=0.789).

	Estimate	Standard Error	z value	p
Intercept	-1.44	1.55	-0.93	0.35
Canopy Cover	6.24	2.78	2.25	0.02
Conspecific Density				
2	-6.87	1.86	-3.70	<0.01
3	-6.24	2.65	-2.35	0.02
4	-5.67	2.50	-2.27	0.02

DISCUSSION

Few bird species have been tracked through time using an acoustic location system disturbance despite findings that this technology improved capacity for monitoring Mexican ant-thrush (Kirschel et al. 2011), and Bornean orangutans (*Pongo pygmaeus wurmbii*; Spillmann et al. 2015). We intended to demonstrate the potential of this approach to determine how ovenbirds responded to vegetation recovery on reclaimed well sites. These singing locations were used to accurately assess habitat quality of reclaimed well sites in absence of a human observer (Wilson et al. 2013). Estimates of individuals using omnidirectional microphones can improve monitoring efforts, yet has been demonstrated in few species (Ehnes and Foote 2015). We demonstrated identification of individuals based on previous data which validated the potential to identify individual ovenbirds using omnidirectional microphones, due to their high individual variation in song (Ehnes and Foote 2015). This allowed us to estimate conspecific density, and account for repeated observations of individuals.

The response of ovenbirds to well site reclamation efforts in previously untested in the western boreal forest. Monitoring small disturbances, including well sites requires precise estimates of bird locations, such as those provided by acoustic localization (Bayne et al. 2016). To understand response to reclamation efforts, it was necessary to account for individual behaviour, in addition to habitat quality. Our predictions that use of well sites would increase with regeneration, and decrease with conspecific density were supported. Our findings support recent trends that accounting for function traits, and behaviour of individuals are necessary for successful reclamation monitoring (Jones and Davidson 2016).

Ovenbirds were an excellent study species using an acoustic location system. Ovenbirds prefer song posts in the lower canopy that are not obstructed to facilitate propagation of their song, therefore error in localization accuracy is limited as songs are produced at similar heights to microphones (Zach and Falls 1978, Wilson et al. 2013). It was not expected that ovenbirds would sing as frequently from reclaimed wells as seen in our study. Although the sample size in this study was modest, results support increasing evidence that ovenbirds can tolerate intermediate levels of disturbance, and will utilize early successional habitats (Hache et al. 2013). The breeding status of birds in this study was unknown, and assessment of reproductive success of individuals which sang from well sites may be necessary prior to determining impacts on well site disturbance on ovenbirds. However, Ovenbirds overlap territories with neighbours up to 60%, and there is evidence that ovenbirds follow an ideal free distribution (Mazzerolle and Hobson 2004, Bayne et al. 2005, Hache et al. 2013). It may be useful to assess how regeneration influences species that partition territories more strongly, and are more sensitive to disturbance to determine impacts of well sites. Many individuals placed a small proportion of singing locations on the well site, with the majority in the adjacent forest. An alternative explanation for inclusion of well sites in ovenbird territories could be greater transmission distances due to decreased density of vegetation in relation to the adjacent forest. Testing this would be challenging, as it would require calibrated sound pressure measurements in different densities of vegetation (Darras et al. 2016).

Acoustic masking of ovenbird songs occurred frequently during the dawn chorus, yet there were sufficient vocalizations available to perform the study. Future studies should survey longer periods of time, and collect more singing locations of ovenbirds to construct territories. Previous studies found that approximately 60 singing locations were required to construct territories for ovenbirds (Zach and Falls 1978). Although localization data is time consuming to process, development of automated species recognition should improve efficacy of this method. Ideally our approach would have been validated or paired with other methods, such as spot mapping or telemetry, as use of song posts alone for ovenbirds underestimated their true territory size (Mazzerolle and Hobson 2004). Following establishment of territories, and association of songs with specific individuals, their behaviour could be determined using localization in absence of human observers by centering smaller arrays which could be processed more efficiently around territories. However, we are confident with our approach of predetermining numbers of individuals, and validating assignment of songs to individuals. Even with small amounts of masking over song clips, and variation in amplitude, use of SPCC was still feasible. Given that ovenbirds display high individual variation in song, and the use of SPCC to discriminate individuals would be not be applicable for species that display less variation and alternative approaches, such as machine learning species recognition algorithms would be required (Kirschel et al. 2009).

Well site reclamation criteria in Alberta does not currently include birds, but current objectives appear to facilitate vegetation recovery, and inclusion of well sites in ovenbird territories. Other metrics, such as foraging observations, and nest success should be used to determine the mechanism behind ovenbird use of reclaimed wells (Jones and Davidson 2016). Localization is an exciting technology that we feel that this method should complement behavioural observations, spot mapping, or telemetry data. Localization should become more accessible with the advent of sensor networks to create more cost effective arrays, and machine learning algorithms to make individual discrimination increasingly time efficient and accurate (Kirschel et al. 2009, Taylor et al. 2016). These data could also be approached using spatially explicit capture-recapture models, or acoustic spatially explicit capture-recapture models to determine density of individuals (Dawson and Efford 2009, Stevenson et al. 2015). Pairing these data, with high resolution photogrammetry or LiDAR data could be used to answer questions on fine scale habitat use, territory establishment, and singing behaviour (van Rensen et al. 2015, Cruzan et al. 2016).

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