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MONITORING AVIAN POPULATIONS WITH ACOUSTIC INDICES IN THE
CENTRAL PLATTE RIVER VALLEY

A Thesis
Presented to the
Graduate Faculty of the Biology Department
and the
Faculty of the Graduate College
University of Nebraska

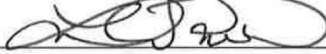
In Partial Fulfillment
of the Requirements for the Degree
Master of Science
University of Nebraska at Kearney

By
Bethany Ostrom
April 2022

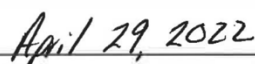
THESIS ACCEPTANCE

Acceptance for the faculty of the Graduate College, University of Nebraska, in partial fulfillment of the requirements for the degree Master of Science, University of Nebraska at Kearney.

Supervisory Committee

Name	Department
	Crane Trust - Science Dept.
	BIOLOGY
	UNL - School of Natural Resources


Supervisory Committee Chair


Date

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ABSTRACT

Acoustic indices are mathematical summaries of sound waves. Several researchers have tried to find relationships between them and vocal animal communities to use them as a passive monitoring method, as human-derived surveys are expensive, time-consuming, and suffer from observer bias. However, supplanting manual surveys with acoustic indices is a daunting task, considering effective indices for biological monitoring would need to differentiate biologically relevant sounds from the broader soundscape, including from human-derived (anthrophony) and earth-derived (geophony) sound. We collected avian community data and calculated six commonly used acoustic indices from acoustic recordings in the largest remaining intact lowland tallgrass prairie in the Central Platte River Valley throughout the breeding seasons of 2019-2021. Singular acoustic indices had only weak correlations with avian abundance, richness, Simpson diversity, and grassland species abundance. Of all avian community metrics, avian species richness was best predicted by the acoustic diversity index (ADI) when a measure of anthrophony was included in the model. The acoustic complexity index and normalized difference sound index also showed promise for use in models for grassland species abundance. We did not find strong evidence for the use of these acoustic indices as a proxy for traditional avian point count surveys, which diverges from much past research related to different ecosystems (i.e., tropical and temperate forests). Intact North American grasslands are declining due to increased agricultural use and urban sprawl, which likely increases the anthrophony in the remaining grasslands. This along with naturally more intense geophony from strong winds in the Great Plains likely creates

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I. INTRODUCTION

Sound influences nearly all of the animal kingdom. Almost every animal has the capability to send and receive auditory signals. Researchers have studied interspecific and intraspecific communication through bioacoustics (Fletcher 2007). However, there are more sounds surrounding us in the soundscape than just sounds produced by animals (biophony). Natural abiotic features and events such as rain, rivers, and wind produce sound (geophony), and sounds propagated by humans and human-made things (anthrophony) also fill the environment and affect animal communities (Pieretti and Farina 2013; Sueur et al. 2014; Villanueva-Rivera 2014). Soundscape ecology is a relatively new and growing discipline (Pijanowski et al. 2011b; Pijanowski et al. 2011a). Whereas other ecological studies of sound focus on communication within species or population levels, soundscape ecology distinguishes itself by focusing on community levels. Instead of focusing completely on biophony, soundscape ecology considers geophony, anthrophony, and how all three interact (Pijanowski et al. 2011a; Sueur et al. 2014). This expanding field of study has the potential to engage patterns of ecosystem complexity in new ways with increased temporal resolution compared to traditional survey techniques (Villanueva-Rivera et al. 2011; Gasc et al. 2017). The soundscape of every environment is waiting to be understood, we just need to listen.

Increasingly, researchers are listening and gathering data from soundscapes using autonomous recording units (ARUs) (Shonfield and Bayne 2017). ARUs provide a cost-effective and non-invasive way to monitor acoustic communities (Alquezar and Machado 2015; Hutto and Hutto 2020; Stewart et al. 2020). Recordings from ARUs have been used

in lieu of in situ avian point-count surveys (Haselmayer and Quinn 2000; Hobson et al. 2002; Hutto and Stutzman 2009; Klingbeil and Willig 2015). This allows ornithologists to listen to and replay audio recordings of surveys to determine species counts producing similar, if not better, results than traditional avian surveys, depending on habitat and recording schedule (Klingbeil and Willig 2015; Alquezar and Machado 2015; Stewart et al. 2020). However, this technique is time consuming with hours spent listening and manually identifying species from recordings.

Automated recognition formulas (classifiers) also work in tandem with ARUs (Zhang et al. 2016; See. Yip et al. 2017, p. 27–67 figure 2). Classifiers recognize specific frequency and/or amplitude patterns that are frequently used to identify avian or anuran species within recordings (Jie Xie et al. 2015; Brauer et al. 2016; Zhang et al. 2016). Once created, a classifier greatly decreases time spent determining presence of a particular species. However, creating a classifier is technically demanding and can be applied only to one species. Commonly, a single species requires multiple classifiers because many species' calls can vary regionally or change due to weather. These challenges limit the ability to quickly study higher levels of biodiversity. Given global environmental transformation (e.g., climate change, habitat loss, land use change, etc.), it is increasingly important to assess ecosystem function with rapid biodiversity assessments in high temporal and spatial resolution, to serve as an objective indicator of biodiversity change and provide early warning signs when ecosystems may be in trouble (Warren et al. 2013; Newbold et al. 2015).

Compared to the previously mentioned methods and traditional surveys of acoustic communities, such as in-person avian point count surveys, Rapid acoustic surveys (RAS) (Sueur et al. 2008b) have the potential to survey multiple locations simultaneously and systematically without species identification by an expert. This may allow for a rapid biodiversity assessment method that is unbiased, cost effective, non-invasive, and applicable to long-term monitoring. This relatively new RAS technique is conducted using ARUs and acoustic indices. Numerous acoustic indices have been developed to facilitate RAS (Buxton et al. 2018); however, acoustic indices only calculate different aspects of acoustic energy within an environment and not necessarily biologically translatable information (Gasc et al. 2013; Sueur et al. 2014; Eldridge et al. 2018). For acoustic indices to be used as an effective monitoring tool, acoustic changes among and within biological communities must be ecologically meaningful, and those changes must be calculatable without being skewed by the remaining soundscape (Sueur et al. 2014; Eldridge et al. 2018). Consensus on how acoustic indices compare to biological community variation has not been reached, and those that have proven occasionally successful need further validation in a diverse set of ecological contexts (Gasc et al. 2015; Eldridge et al. 2016; Ferreira et al. 2018; Moreno-Gómez et al. 2019).

The acoustic complexity index (ACI) (Pieretti et al. 2011) was created in response to other acoustic indices being too sensitive to background noise. ACI measures changes in frequency that in theory correspond to avian calling diversity while ignoring constant noises such as traffic or wind. ACI positively correlated in multiple studies with avian abundance (Pieretti et al. 2011; Izaguirre and Ramírez-Alán 2018; Jorge et al. 2018;

Eldridge et al. 2018; Brinley Buckley et al. 2018) and negatively correlated with diversity and richness (Pieretti and Farina 2013; Mammides et al. 2017; Izaguirre and Ramírez-Alán 2018; Shamon et al. 2021). Even though ACI has had considerable success, Gasc et al. (2015) did not think ACI would be a good proxy for monitoring richness considering ACI was sensitive to background noise amplitude changes and chorus composition. Shamon et al. (2021) also encouraged careful interpretation of ACI suggesting ACI would positively correlate with high diversity of species with shorter more variant calls despite their findings of negative correlation to diversity in grassland habitats where avian calls were longer with more overlap.

The bioacoustic index (BIO) (Boelman et al. 2007) was created to represent relative avian abundance by calculating the area under the mean spectrum (in dB) minus the minimum intensity of the curve between 2–8 kHz (Fuller et al. 2015, Izaguirre and Ramírez-Alán 2018, Bradfer-Lawrence et al. 2019). BIO was found to correlate with avian abundance (Boelman et al. 2007; Fuller et al. 2015; Izaguirre and Ramírez-Alán 2018; Jorge et al. 2018) and was the best individual index to predict avian richness (Eldridge et al. 2018; Shamon et al. 2021). However, Mammides et al. (2017) found only a weak correlation between BIO and avian richness. When modeled with other indices to show temporal and spatial patterns, BIO was the least influential index included (Bradfer-Lawrence et al. 2019), and BIO showed no patterns following any vocal taxa (Ferreira et al. 2018). Fairbrass et al. (2017) found BIO to be useful for determining biotic diversity and activity in urban areas, but it was influenced by human voices.

Acoustic entropy index (H), loosely based off of Shannon Entropy Index (Shannon and Weaver 1949) was created by Sueur et al. (2008b) to test alpha diversity of avian communities. Sueur et al. (2008b) had success testing H in a Tanzanian coastal forests. However, due to higher ratios of anthrophony to biophony success with H in temperate locations has been limited (Depraetere et al. 2012). This is in part due to high sensitivity to background noise which causes false high readings of H.

Previously mentioned indices have been created with the intention of analyzing some aspect of biodiversity. Multiple indices also have been created to monitor habitat condition. The normalized difference sound index (NDSI) estimates habitat condition by calculating the ratio of anthrophony to biophony (Kasten et al. 2012). Fuller et al. (2015) found NDSI to strongly correlate with biocondition. They also found patterns between the index and bird richness, where higher richness produced more consistent values and lower richness more variable values for NDSI. NDSI was correlated with avian richness and diversity as well as anthrophony and was suggested as a measure of disturbance (Fairbrass et al. 2017).

The acoustic diversity index (ADI) and the acoustic evenness index (AEI) (Villanueva-Rivera et al. 2011) are meant to help interpret the degree of degradation of a habitat by calculating the diversity and evenness of a soundscape. In a theory tested by Villanueva-Rivera et al. (2011), a generally unaltered habitat should have a more even soundscape with most frequency bins occupied, and an altered habitat will be more uneven sonically due to gaps in biophony. Villanueva-Rivera et al. (2011) documented this pattern where more agricultural landscapes had a lower ADI and higher AEI, and

more forested habitats had a lower AEI and higher ADI, indicating the indices correctly assessed the forested habitats to be more intact than the agricultural landscapes. Fuller et al. (2015) found AEI to negatively correlate with biocondition, which is expected, but did not find any patterns for ADI. ADI and AEI had nonlinear relationships, opposite of each other, for vegetation cover gradients (Shamon et al. 2021). ADI and AEI also have been tested as proxies of biodiversity with some success showing significant correlations with biodiversity estimates (Eldridge et al. 2018). ADI was shown to correlate strongly with anuran communities but weakly with avian communities, and the opposite was true for AEI (Ferreira et al. 2018). However, Jorge et al. (2018) found ADI to have a negative correlation with avian diversity.

The inconsistencies between acoustic index study results could be due to acoustic indices not only considering the biotic community or taxa of interest, but also the whole soundscape. While this has possibly inhibited index performance (Ferreira et al. 2018; Moreno-Gómez et al. 2019), Eldridge et al. (2018) found that acoustic indices may provide a more comprehensive and nuanced evaluation of biodiversity than traditional survey methods. However, the success of acoustic evaluation of biodiversity may be limited by ecosystem type. Multiple studies testing acoustic indices have been done in temperate (Depraetere et al. 2012; Gasc et al. 2015; Farina et al. 2016; Eldridge et al. 2018; Shamon et al. 2021) or tropical forests (Boelman et al. 2007; Towsey et al. 2014; Mammides et al. 2017; Ferreira et al. 2018; Izaguirre and Ramírez-Alán 2018; Eldridge et al. 2018), with varying degrees of success. It has been shown that acoustic indices currently reflect temperate habitat biodiversity more successfully than tropical habitats

(Eldridge et al. 2018). This is thought to be caused by the difference in number of vocalizing taxa between the two ecosystems. However, acoustic indices were able to decipher the location of recordings better than avian point-count surveys in tropical forests (Eldridge et al. 2018).

While acoustic indices have been tested in various environments, most acoustic index studies have been conducted in forest habitats. It is known that avian species living in forests have different song characteristics than birds in grasslands (Boncoraglio and Saino 2007; Shamon et al. 2021), which could affect acoustic indices effectiveness in unknown ways. Very few studies have researched the effectiveness of acoustic indices in grasslands (Shamon et al. 2021). RAS may offer opportunities to assess grassland birds that are rapidly declining (Rosenberg et al. 2019). Adopting RAS as a monitoring technique could allow for wildlife and land managers to quickly be notified of changes in avian populations and respond accordingly before further population decreases occurred.

However, grasslands are subject to direct and frequent winds linked to ecosystem maintenance that severely affect the soundscape and recordings used for data (Brinley Buckley et al. 2018; Hanberry 2021). Acoustic indices may respond differently in grasslands purely because of wind. While urban sprawl is widespread, grasslands also may be more affected by urbanization sonically due to anthrophony traveling farther because there are fewer natural barriers. So acoustic index results may be altered by sources of nearby anthrophony and need to be interpreted appropriately.

Many studies testing this relatively new RAS technique have determined diversity of the environment by conducting “recorded avian surveys,” listening to recordings to

determine species count (Haselmayer and Quinn 2000; Hobson et al. 2002; Hutto and Stutzman 2009). This technique has been shown to be comparable to traditional in-person avian point count surveys. However, if RAS are adopted as an efficient monitoring method, they most likely would not be conducted in the same manner as traditional surveys (Klingbeil and Willig 2015). ARUs can easily be set to record multiple times a day instead of once every few days or weeks like many in-person monitoring plans. To test true potential of RAS through acoustic indices, ground truthing is needed to determine species richness, total abundance, and Simpson diversity (SDI; 1-D) (Simpson 1949) of bird populations through traditional means in relation to new sampling methods utilizing ARUs. The Central Platte River Valley (CPRV) is an ideal location to gather grassland avian community data due to it being critical breeding grounds for a diversity of grassland birds throughout a range of riverine and grassland habitats (Brown and Johnsgard 2013).

We raise the question of how well individual and combinations of acoustic indices, including ACI, AEI, ADI, BIO, H, NDSI, can predict species richness, total abundance, and SDI of bird populations in the Central Platte River Valley as measured via traditional monitoring methods like point count surveys?

H₀: Acoustic indices from sound recordings do not predict species richness, total abundance, and SDI of bird populations measured via traditional active monitoring such as point-count surveys.

H_a: Acoustic indices from sound recordings can predict species richness, total abundance, and SDI of bird populations measured via traditional active monitoring such

at point-count surveys, and thus may be useful as a proxy for assessing avian abundance and community composition dynamics.

II. METHODS

A. Study Site

Our research was conducted within the Central Platte River Valley (CPRV) in south-central Nebraska, USA. The Platte River is greatly modified from historical conditions. In the 1800s, the Platte River was described as “a mile wide and an inch deep”. The wide, yet shallow river and high water table promoted growth of wet meadows, tallgrass prairie, and riparian woodlands within the river valley (Chen 2007). However, dams and diversions, surface and ground water extraction for irrigation, and other human influences have dramatically decreased the river’s flows and floodplain connectivity, leading to woody encroachment, bank stabilization, and narrowing of channels (Williams 1978; Johnson 1994; Currier 1997; Farnsworth et al. 2018; Caven et al. 2019). Much of the land that was once wet meadow and native prairie has been converted to cropland (Dappen et al. 2008). Even though river channel area has decreased more than 46% and active channel width more than 59% on average since 1938 (Horn et al. 2012; Appendix 2, Caven et al. 2019), the Platte River still has occasional high flows and a high water table with variations of elevation creating a mosaic of ecotopes ranging in moisture levels, plant communities, and soil types (Henszey et al. 2004; Chen 2007; Brinley Buckley et al. 2021). With wet meadows, tallgrass prairies, ephemeral and perennial sloughs, shrublands, riparian woodlands, sandy ridges, and river sandbars all within a relatively short distance, the CPRV is a globally recognized Important Bird Area

providing stopover habitat for a diversity of migrating and breeding birds (Lingle and Hay 1982; Sharpe et al. 2001; Brown and Johnsgard 2013; Poague 2016).

Most of our sampling sites were located on land owned by the Crane Trust (40.7887873, -98.4681745; 585 m.a.s.l.), a nonprofit conservation organization near Grand Island, NE, focused on managing land within the CPRV for migrating and breeding birds, including the endangered Whooping Crane, with adaptive management techniques such as prescribed burning and rotational grazing of cattle and bison to mimic natural historical disturbance regimes (Fuhlendorf et al. 2009). Within Crane Trust property, our sites were centered on Mormon (40.7959911, -98.4149933; 578 m.a.s.l.) and Shoemaker (40.7887872, -98.4681745; 585 m.a.s.l.) islands (Figure 1a). One additional site was west of Crane Trust land, located a restored wetland at the Kearney Outdoor Learning Area (40.67754, -99.12228; 658 m.a.s.l.) (Figure 1b).

B. Data Collection

We collected audio and avian data during springs and summers of 2019, 2020, and 2021. We used autonomous recorders with two microphones (Song Meter SM2+ and SM4; Wildlife Acoustics, Maynard, Massachusetts, USA) to capture 5-minute recordings of avian populations every hour. The sampling rate was 44.1 kHz and the bit depth was 16 bits. We set the audio recorders at specific locations based on terrestrial monitoring plots from the Crane Trust's long-term research and monitoring plan used to monitor vegetation, bird diversity and relative abundance, anuran populations, small mammal populations, and butterfly species of concern throughout the CPRV at varying ecotopes (soil and plant communities) (Caven et al. 2017). Recorders were serviced approximately

monthly to exchange SD cards, replace batteries, and ensure they were working properly. SD cards were downloaded to a file organized by individual recorder and date.

Avian point-count surveys were conducted at each monitoring plot within 400 m of an audio recorder at least twice within the breeding seasons (21 May to 15 July) 30 minutes before sunrise to 3 hours after sunrise (Sorace et al. 2000; Gregory et al. 2004). Two surveyors completed the 15-minute surveys with one as an observer and one as a recorder. During the survey time, the observer identified each bird seen or heard in the area and indicated it as within a 50-m radius of the observer (herein referred to as “in”) or not. The recorder also assisted with bird detection and identification as necessary. Temperature, wind speed, and wind direction were recorded at the beginning or end of the survey with a Kestrel 3500 Weather Meter. Surveys were not conducted if the temperature was below -2.2° C (28° F), wind was over 24.1 kph (15 mph), there was fully overcast skies, moderate or heavy rain occurring, or visibility reduced by fog (Sorace et al. 2000; Gregory et al. 2004).

Recordings used for avian analysis included three, 5-min recordings from the same day that the manual surveys were conducted to have equal time allotments for both methods (15 minutes). The three, 5-min recordings used were within the time parameters allowed for manual avian surveys (i.e., within 3 hrs. of sunrise). This method was a compromise between the two sampling methods that Klingbeil and Willig (2015) used that resulted in suggesting to record more frequently over a longer amount of time to alleviate the loss of visual detection of birds.

C. Analyses

We used R (version 4.1.1) and R-Studio (version 1.4.1717; R Core Team 2021) for analyses. We calculated six acoustic indices from the R packages ‘seewave’ (version 2.1.8; Sueur et al. 2008a) and ‘soundecology’ (version 1.3.3; Villanueva-Rivera et al. 2011). Acoustic Complexity Index (ACI) (Pieretti et al. 2011) calculates the variability of the soundscape by accounting for the complexity of vocal biotic communities despite constant sounds produced by humans, known as anthrophony. This relies on the idea that biotic sounds are generally characterized by variation of intensity, whereas anthrophony is generally consistent in intensity. This is done by considering the amplitude of one-time sample’s frequency band versus the amplitude of the next time sample’s frequency band and the relative amplitude of the entire band. Acoustic Diversity Index (ADI) (Villanueva-Rivera et al. 2011) is able to calculate the evenness of a soundscape or if there is equal intensity throughout all or most frequency bands. In theory, acoustically rich habitats would produce higher values because all or most frequency bands are constantly occupied. ADI essentially calculates the Shannon diversity index for a sound file. Acoustic Evenness Index (AEI) (Villanueva-Rivera et al. 2011) calculates the unevenness of a soundscape or if there is a greater intensity within a specific range of frequency. It will produce higher results if there is greater unevenness between frequencies, like the Gini coefficient (opposite of ADI). In theory acoustically rich habitats would produce values closer to 0 since all or most frequency bands are constantly being occupied. Bioacoustic Index (BIO) (Boelman et al. 2007) was created to track large changes in avian communities among habitats (not accounting for changes in

probability of detection) or through time. It is calculated by looking at the average amplitude within a specific range of frequency bands minus the band with the lowest amplitude. Acoustic Entropy Index (H) (Sueur et al. 2008b) was created using temporal entropy (Ht) and the spectral entropy (Hf) with the goal of measuring alpha diversity. H is calculated based on Shannon entropy of probability mass function where Ht is derived from the amplitude envelope and Hf from the mean spectrum. Normalized Difference Sound Index (NDSI) (Kasten et al. 2012) is considered to calculate the ‘health’ of the habitat, looking at the ratio of anthrophony to biophony or $(\text{biophony} - \text{anthrophony}) / (\text{biophony} + \text{anthrophony})$ where anthrophony is anything within 1–2kHz and biophony is 2–11kHz. NDSI has potential to show the long-term relationship between biophony and anthrophony, but not diversity within a habitat. ACI, ADI, AEI, BIO, H, and NDSI are commonly used in other studies and were chosen in order to have a stronger comparison to other research (Bradfer-Lawrence et al. 2020).

Our outcome variables were calculated from the avian point count surveys and consisted of avian richness (number of bird species); absolute avian abundance (number of individual birds); Simpson diversity (SDI; accounts for number of species present and relative abundance of each species; Simpson 1949), which was calculated using the default in the package ‘vegan’ (version 2.5-7; Oksanen et al. 2020); and grassland species abundance, which consisted of a count of obligate grassland bird species (Upland Sandpiper, Grasshopper Sparrow, Dickcissel, Bobolink, Red-winged Blackbird, Western Meadowlark, and Brown-headed Cowbird; Kim et al. 2008). Our avian survey method allowed us to calculate two variations of each outcome variable, one consisting of survey

results with a limited radius of 50 m (“in”) and one consisting of survey results with an unlimited radius (“total”). This was done to test if acoustic indices would work better at a local scale or more expansive scale due to limited natural sound barriers in the grasslands. Akaike's Information Criterion corrected for small sample sizes (AICc) (Wagenmakers and Farrell 2004; Burnham et al. 2011) was used to compare models, and McFadden's Pseudo- R^2 (McFadden 1974) was used to assess goodness of fit of best models.

In addition to survey results and acoustic indices, we documented environmental and temporal variables including: wind speed at time of survey (WIND); whether wind was from the north (NORTH; yes/no), because wind could carry noise from the interstate that was north of most audio recorders and the greatest source of nearby anthropony; shortest distance from interstate to the audio recorder (DIST_INTERSTATE), Julian date (JD), temperature at time of survey (TEMP), and time of survey (TIME). We also considered interactions between DIST_INTERSTATE and acoustic indices and WIND and acoustic indices because anthropony and geophony generally affect acoustic indices (Towsey et al. 2014; Fuller et al. 2015; Buxton et al. 2018). We controlled for observer bias during bird surveys, audio recorder model, and distance from audio recorder to avian point count location (monitoring plot) in each model tested. We used ACI, ADI, AEI, BIO, H, NDSI, WIND, NORTH, DIST_INTERSTATE, JD, TEMP, and TIME as predictor variables in generalized linear models (GLMs) (Nelder and Baker 1972) to determine which variables were most influential in predicting the outcome variables: richness in and total, abundance in and total, SDI in and total, grassland bird abundance

in and total within our ecosystem. Global models were fit and assessed to ensure they fit the assumptions of GLMs. Variables with a moderate or high Pearson's correlation ($r > 0.6$; Chan 2003) were not included in the same global model.

To compare relationships between acoustic indices and avian community metrics, we determined models of best fit using Akaike's Information Criterion corrected for small sample sizes (AICc) (Wagenmakers and Farrell 2004; Burnham et al. 2011). Our model set included three subglobal models, models derived from backwards selection of the three subglobal models, models derived from the literature as to which acoustic indices were suggested to work the best, and thematic models to test if anthrophony and geophony influence acoustic index readings directly. Pearson's correlations were also run for acoustic indices and avian outcome variables to determine if any linear relationships were present in the data. We used Chan (2003) to define correlation thresholds (strong, $r \geq 0.8$; moderate, $r \geq 0.6$; fair, $r \geq 0.3$; and poor, $r < 0.3$).

The confidence set for each outcome variable was determined by including the top weighted models until the AICc cumulative weight was at least 0.95. Because model uncertainty is common, model averaging of the confidence set was done to determine variable significance (Rehme et al. 2011). Model averaged variables and interaction terms were then plotted against the outcome variable with 95% confidence intervals to further determine relationships between acoustic indices and avian community metrics. McFadden's Psuedo- R^2 (McFadden 1974) was calculated for each model in the confidence set and then averaged to determine which method of surveys was a better fit for acoustic indices.

III. RESULTS

We completed and paired 18, 31, and 44 surveys with audio recordings in the breeding seasons of 2019, 2020, and 2021 respectively for a total of 93 avian point-count surveys at 21 sites. Over these 3 seasons, we surveyed a total of 73 different bird species. The most abundant species were Red-winged Blackbird (*Agelaius phoeniceus*), Brown-headed Cowbird (*Molothrus ater*), Dickcissel (*Spiza americana*), Bobolink (*Dolichonyx oryzivorus*), and Western Meadowlark (*Sturnella neglecta*) (Appendix A). We had up to 22 different bird species and 155 individuals in one point count survey (Table 1). We analyzed 279 5-min audio recordings to produce the 6 acoustic indices for each survey completed. ACI ranged from 8,986 to 13,077 with an average of 9,805 (Table 1). ADI ranged from 0.262 to 2.251 with an average of 1.581. AEI ranged from 0.162 to 0.877 with an average of 0.539. BIO ranged from 3.08 to 13.41 with an average of 7.30. H ranged from 0.279 to 0.983 with an average 0.703. NDSI ranged from -0.539 to 0.983 with an average of 0.730 (Table 1).

A. Correlations

None of the avian community metrics were strongly or moderately correlated with any of the acoustic indices (Table 2; per Chan 2003). The highest correlation was between ADI and abundance with an unlimited sampling radius; the correlation was highly significant but only of fair strength (0.325; Table 2). All remaining significant correlations were only of poor strength (Table 2). Abundance, both within 50 m and with an unlimited sampling radius, was correlated positively with ADI and H, and negatively

with AEI. Richness with an unlimited sampling radius had a negative correlation with ACI. SDI, both within 50 m and with an unlimited sampling radius, was not significantly correlated with any acoustic indices. Grassland species abundance within 50 m was positively correlated with ACI, ADI, BIO, as well as negatively with AEI. Grassland species abundance with an unlimited sampling radius was positively correlated with ACI.

There were many significant and relatively strong correlations between the acoustic indices (Table 3). AEI was highly and moderately negatively correlated with ADI and H, respectively, while ADI and H were moderately positively correlated. Fair positive associations occurred between ACI and ADI, ADI and NDSI, and BIO and NDSI. Fair negative associations occurred between AEI and ACI, as well as NDSI and AEI (Table 3).

Some avian community variables and temporal predictor variables were correlated (Table 4). Abundance within 50 m had a poor negative correlation with wind speed. Richness with an unlimited sampling radius and grassland species abundance within 50 m had poor positive and negative correlation to date, respectively. Richness with an unlimited sampling radius was also poorly negatively associated with a northerly wind component and positively correlated to temperature. Distance to the interstate was significantly correlated with richness and SDI, and negatively correlated with grassland species abundance, both within 50 m and with an unlimited sampling radius for each (Table 4).

There were few correlations between acoustic indices and temporal predictor variables (Table 5). ACI had highly significant fair negative correlations with date and

distance to interstate (Table 5). ADI and AEI were fairly negatively and positively correlated to wind speed, respectively. BIO had poor negative correlations to date and temperature. H had a poor positive correlation to a northerly wind component and NDSI had a poor positive correlation to temperature (Table 5)

B. Richness

Avian richness within 50 m was a better fit to the acoustic index data than avian richness with an unlimited sampling radius due to a higher average pseudo R^2 value (Table 6). The top model for avian richness was ADI and distance to interstate (Table 7). Considering ADI and AEI were highly correlated, it was not surprising that the second model with a weight of 0.33 was AEI and distance to interstate. However, the model averaging results showed that ADI and AEI did not have significant predictive power in the top models (Figure 2), whereas distance to interstate was very significant in the top models (Table 8). Despite model averaging showing otherwise, ADI and AEI must have explained some slight variation in the data because distance to interstate alone was only the third best model (Table 7). Considering all of this, our richness models did not explain much variation in the data shown by the lower pseudo R^2 . However, our richness models did have the highest pseudo R^2 out of all the avian community metrics (Table 6).

C. Abundance

Avian abundance within 50 m had the better psuedo- R^2 compared with abundance with an unlimited sampling radius (Table 6). Our abundance models ranked 3rd in psuedo- R^2 out of the four avian community metrics and had low goodness of fit to the data. The model with the best AICc for avian abundance consisted of AEI and ACI with

the interactions with distance to interstate and NDSI and its interaction with wind speed (Table 9). The model with the highest pseudo- R^2 consisted of BIO and ACI and their interaction with wind speed, H, time of survey, and NDSI with its interaction with wind speed and distance to interstate (Table 9). H by itself had the 3rd best AICc but it presented the worst pseudo- R^2 within the confidence set (Table 9). The remaining two models in the confidence set for abundance had a combined AICc weight of 0.05. Model averaging showed limited significance with any one variable or interaction term (Table 10, Figures 3, 4, and 5).

D. Simpson Diversity

Avian SDI with an unlimited sampling radius models were better fit to our acoustic index data than SDI within 50 m (Table 6). SDI was the only metric that our total counts performed better than our counts within 50 m. However, the pseudo- R^2 was negative for both indicating our models did not fit the data. Our SDI models had the lowest pseudo- R^2 out of all avian community metrics (Table 6). Our best models for SDI consisted of ADI, NDSI, and their interaction with distance to interstate along with date (Table 11). Both models in the confidence set were similar in model weight attributing to high model uncertainty. Based on model averaging date, NDSI, and NDSI: DIST_INTERSTATE were significant (Table 12, Figures 6 and 7).

E. Grassland Species Abundance

Grassland species abundance within 50 m fit our data better than grassland species abundance with an unlimited sampling radius (Table 6). Grassland species abundance was the second best fit to our data for avian community metrics (Table 6). The

confidence set for grassland species abundance only consisted of one model with a high model weight (Table 13). Considering model uncertainty was low, model averaging was not needed, and ACI, NDSI, date, distance to interstate, ACI:DIST_INTERSTATE, and NDSI:DIST_INTERSTATE were all significant (Table 14). However, Figure 8 shows that NDSI and ACI by themselves have minimal power to predict grassland species abundance, but when the interaction with distance to interstate is considered, a relationship between the acoustic indices and grassland species abundance becomes more evident (Figure 9). ACI has a negative relationship with grassland species abundance when closer to the interstate, but that relationship inverts as the interstate becomes further away (Figure 9a). NDSI seemed to only have a significant positive relationship with grassland species abundance when closest to the interstate (Figure 9b). At maximum and average values, the relationship was not significant (Figure 9b).

IV. DISCUSSION

We tested how well six commonly used acoustic indices can be used for avian monitoring within a temperate grassland. Many studies have considered the efficacy of acoustic indices as a proxy for biodiversity monitoring (Farina et al. 2016; Ferreira et al. 2018; Jorge et al. 2018; Buxton et al. 2018; Eldridge et al. 2018; Zhao et al. 2019; Bradfer-Lawrence et al. 2020; Shamon et al. 2021), but only a few indices have been tested with ground-based avian data from in-person surveys (Jorge et al. 2018; Müller et al. 2020; Bradfer-Lawrence et al. 2020; Dröge et al. 2021), and fewer still have considered grasslands as the test setting (Shamon et al. 2021). Our study provided insights about how well acoustic indices may relate to in-person avian call surveys

conducted in a grassland system in the Great Plains of North America. Our results indicated relatively low success using singular acoustic indices to identify variation in the bird community across sites in grasslands of the CPRV when looking at correlations between acoustic indices and avian community metrics alone. While we did find significant correlations between acoustic indices and in-person avian survey, they were only slight or weak ($r < 0.45$, Table 2), which indicates that single acoustic indices were not suitable for use for avian monitoring in our grassland study area as a proxy for manual point-count surveys. Because we found significant but weak correlations, there is potential singular acoustic indices could follow long-term trends in avian data if a baseline relationship between the acoustic index, habitat, and avian community is understood prior to monitoring. For example, we found ADI to have a significant correlation to avian abundance sampled with an unlimited radius in our study system, but ADI only follows about 30% of the changes in avian abundance (Table 2). This relationship would not efficiently show minute changes in avian abundance, but it could suggest dramatic or large-scale changes in the avian community. This relationship may be different in other study systems, which is emphasized by the extreme variation in performance and results of acoustic indices between and within other studies (Mammides et al. 2017; Ferreira et al. 2018; Eldridge et al. 2018; Bradfer-Lawrence et al. 2020; Mammides et al. 2021).

We found ACI to have a poor negative relationship with total avian richness and a poor positive relationship with both grassland species abundance variables (Table 2). Others have found significant positive relationships with richness and ACI (Eldridge et

al. 2018; Bradfer-Lawrence et al. 2020). However, many also have found a negative or extremely weak or nonexistent relationship between avian richness and ACI (Ferreira et al. 2018; Moreno-Gómez et al. 2019; Zhao et al. 2019; Dröge et al. 2021; Shamon et al. 2021), including Eldridge et al. (2018) in tropical forests. A negative relationship with ACI indicates that the soundscape has more even intensity at lower richness, and there is a more inconsistent intensity in the soundscape at higher richness. This is the opposite of basic theories of RAS connecting avian diversity, habitat health, and the soundscape (Sueur et al. 2008b; Villanueva-Rivera et al. 2011). This would mean ACI may not be a measure of biodiversity but instead may just act as relative measure of avian activity after establishing a baseline within a specific location. This is considering that Ferreira et al. (2018) found ACI's relationship to vary between locations (negative at one location and positive at another), and ACI did not have a significant relationship with any vocal animal group unless results were separated by site (Ferreira et al. 2018). This could be why we did not find strong or consistent results for ACI as we did not distinguish between sites.

ACI was designed to have a positive relationship with avian singing intensity (Pieretti et al. 2011). Researchers have found ACI correlated with a number of vocalizations (Farina et al. 2011; Depraetere et al. 2012; Fuller et al. 2015), which follows the intended purpose of relating to singing intensity. An interesting case found ACI to negatively correlate to diversity and richness but positively to abundance (Izaguirre and Ramírez-Alán 2018). We found grassland species abundance to have a significant weak positive correlation, which could indicate that ACI was a better measure

of abundance than richness considering grassland ecosystems and/or associated birds. Also, despite our low correlations with avian richness, ACI was only influential in models associated with avian abundance and grassland species abundance. Since increased richness does not necessarily indicate an increase in song intensity or number of vocalizations, it tracks that ACI has had relatively limited success in accounting for avian richness (Ferreira et al. 2018; Zhao et al. 2019; Dröge et al. 2021) and was not included in any of our top models for diversity or richness in our study area. Bradfer-Lawrence et al. (2020) found ACI to not perform better with avian richness compared to avian abundance. This further indicates that considering the design of ACI when deciding where to apply ACI is critical to the success of the index.

ADI and AEI had the most success with our avian abundance variables but still only showed poor or fair relationships (Table 2). Despite the correlations with abundance, they were the only acoustic indices to be included in the avian richness confidence set, indicating that ADI and AEI have the most promise to relate to richness, especially in grasslands. However, there are inconsistent relationships between ADI, AEI, and avian communities throughout literature even within North American grasslands (Shamon et al. 2021). A more consistently filled frequency spectrum (higher ADI values, lower AEI values) has been shown to relate to habitats with both lower (Eldridge et al. 2018; Moreno-Gómez et al. 2019; Bradfer-Lawrence et al. 2020) and higher levels of avian diversity (Sueur et al. 2008b; Mammides et al. 2017; Zhao et al. 2019; Mammides et al. 2021). This may indicate a limited utility for both ADI and AEI. However, this in fact emphasizes the need to carefully interpret the results of ADI and AEI in the context of a

unique habitat. Mammides et al. (2021) explains how AEI (and conversely ADI) can realistically produce a negative or positive relationship with biodiversity depending on the frequency range of the birds singing and the level of background noise or anthrophony in the soundscape.

We found relationships opposite that of Bradfer-Lawrence et al. (2020) for ADI and AEI. Considering Mammides et al. (2021), this could mean our habitat is more consistently filled with lower frequency anthrophony and is affecting the results of ADI and AEI differently than in a habitat with a pristine soundscape. Considering this, it makes sense why our top models for avian richness (also best models overall) only included ADI or AEI and distance to major source of anthrophony (interstate to the north). This is yet another example of how acoustic indices can be used only if the effects of the surrounding environment on acoustic indices are understood before interpreting the results.

We only found a poor positive relationship for BIO with grassland species abundance within 50 m. Shamon et al. (2021) found BIO (referred to as BI) to have a weak significant correlation to avian richness in grasslands. However, others have found negative relationships between BIO and avian richness (Zhao et al. 2019) and diversity (Izaguirre and Ramírez-Alán 2018). However, we found BIO to be influential only in avian abundance top models and not in richness or diversity models. Ferreira et al. (2018) more broadly concluded that BIO was not correlated to any biophony-type richness, especially avian, and accounted for biophonic abundance rather than richness. This follows with BIO's intended purpose and original success of being a measure of avian

abundance by considering intensity and diversity of frequency in a recording (Boelman et al. 2007). Again, despite the considerable attempts to use BIO as a measure of avian richness (Mammides et al. 2017; Eldridge et al. 2018; Zhao et al. 2019; Bradfer-Lawrence et al. 2020; Shamon et al. 2021), our results suggest that BIO, like ACI, is better suited to follow patterns of avian abundance in grasslands in the Central Platte River Valley. These findings are counter to Bradfer-Lawrence et al. (2020) who found BIO to better fit with richness data than abundance models.

We did not find any correlation between H and richness, which instead demonstrated a significant, but poor, correlation with avian abundance (Table 2). H had the strongest correlation with avian richness in a controlled simulated experiment (Zhao et al. 2019) and was significantly correlated to richness in a subtropical region (Fuller et al. 2015). Yet H was found to weakly negatively correlate with avian richness but was a better positive fit for anurans and insects (Ferreira et al. 2018) or even have no correlation to avian richness (Jorge et al. 2018). H has been reported to be strongly affected by background noise (Depraetere et al. 2012; Gasc et al. 2015). Considering our soundscape had a nearby source of anthrophony from the interstate, H may not have performed as efficiently as in other studies (Sueur et al. 2008b; Zhao et al. 2019).

NDSI was an interesting case, as we did not detect significant relationships between any avian community metrics and NDSI based on correlations, but NDSI was the most common acoustic index within our top models except for richness models. NDSI was created and found to calculate level of sonic disturbance and categorizes types of sounds into distinct frequency bins (anthrophony; 0.2-2kHz, biophony; 2-8kHz) (Kasten

et al. 2012; Fairbrass et al. 2017). When NDSI was included our top models, it was typically interacting with the variable related to a major source of anthropony and/or wind speed. Figures 5c, 7b, and 9b show that the relationship between NDSI and the avian community changes based on the level of anthropony and/or geophony and may explain why there were no correlations with avian community metrics. NDSI also increased significantly as did distance to highway (Ghadiri Khanaposhtani et al. 2019). However, Ghadiri Khanaposhtani et al. (2019) did not attribute this entirely to changes in anthropony as other acoustic indices and avian survey results indicated changes in biophony as well which would affect NDSI results. NDSI was also found to follow patterns of biocondition (which considered proximity to road) where a lower biocondition resulted in a more variable NDSI result (Fuller et al. 2015). This indicates that if NDSI is used for acoustic monitoring in grasslands, measures of anthropony and/or geophony should also be considered, otherwise NDSI may not produce interpretable results directly related to avian community changes.

Studies have found that some indices work differently with higher levels of anthropony (Buxton et al. 2018). Anthropony seems to elevate most acoustic index readings (Fuller et al. 2015). However, the exact expected effects of anthropony on acoustic indices is difficult to define because birds may sing louder in habitats with consistent anthropony, which should also increase acoustic indices such as ACI (Pieretti and Farina 2013) or bird communities, especially in herbaceous wetlands, may change due to nearby sources of anthropony (Ghadiri Khanaposhtani et al. 2019). ACI was shown to have a negative relationship with distance to anthropony despite changes in

avian richness (Pieretti and Farina 2013). Conversely, ACI had a negative relationship to anthropony intensity (Gasc et al. 2015). NDSI had a positive relationship with distance to anthropony (Ghadiri Khanaposhtani et al. 2019). However, being able to distinguish between changes in acoustic index results caused by an increase in singing intensity or an increase in anthropony intensity is difficult to determine, especially for indices that calculate sound intensity rather than frequency. This difficulty is amplified by our conflicting results. Our grassland species abundance models showed the strongest interactions with acoustic indices and anthropony (Figure 9), where at the average distance from the interstate NDSI and ACI had positive or nearly positive relationships with grassland bird abundance (Table 14). Closer to the source of anthropony the relationship between grassland bird abundance and NDSI became more positive, and ACI's relationship became increasingly negative. The opposite was true when anthropony was farther away; the relationship with NDSI was negative and the relationship with ACI was positive (Figure 9).

Geophony has been found to cause acoustic indices to perform poorly (Towsey et al. 2014). Wind was included in multiple top models in our abundance and grassland species abundance confidence sets (Tables 10 and 14). This indicates that wind is an important consideration when assessing biophony in soundscapes and should generally be included as a control variable in models intending to assess biological communities with acoustic indices, especially in open and windy environments. This may be particularly important in the Great Plains and other grassland provinces (Hanberry 2021).

We found that our acoustic index models best predicted avian richness when monitoring avian populations in grasslands. While this has not been strictly determined in past research, as only a few studies have compared measures of avian biodiversity other than richness (Boelman et al. 2007; Pieretti et al. 2011; Izaguirre and Ramírez-Alán 2018), many have already compared avian richness to acoustic indices (Gasc et al. 2015; Fuller et al. 2015; Mammides et al. 2017; Jorge et al. 2018; Eldridge et al. 2018; Shamon et al. 2021). However, our model for grassland species abundance exhibited more promise than expected as it was the second-best model set after richness (Table 6). The top five most abundant birds were all grassland species (Appendix A). Grassland species are thought to sing with higher frequencies as they travel farther than lower frequencies and there are not as many natural barriers to block high frequency sounds (Cosens and Falls 1984). The more frequent and higher frequency songs considered in the grassland species abundance metric may explain why ACI and NDSI were the acoustic indices used in the model. The higher frequency songs of grassland birds would be less likely to intermix with the lower frequencies of the anthrophony creating a cleaner ratio of biophony to anthrophony for NDSI to calculate. Because grassland birds were the most abundant, ACI was most likely able to detect intensity changes alongside grassland species abundance changes. Shamon et al. (2021) also had success with ACI and grassland species and did not find a strong relationship with ADI and AEI.

All our acoustic index models in the final confidence sets performed better when the outcome variable related to survey results with a limited radius, excluding avian Simpson diversity that performed poorly. While richness was best fit to our data and

grassland species abundance not far behind (Table 6), we did not reach a level of Psuedo- R^2 high enough to suggest that acoustic indices are a good proxy for in person avian point-count surveys yet. However, with a greater understanding of the surrounding habitat and how it affects acoustic index models, acoustic indices may be able to report avian diversity trends for long-term monitoring and research. However, this will likely require a model-based framework with multiple indices as predictor variables. Additionally, the most appropriate indices for monitoring may need to be regionally specific to reflect the local biota as well as geophony and anthrophony. Finally, it may be necessary to increase the number of control variables including habitat features that may influence sound transmission.

Limitations

While our study area was mostly grasslands, there were survey and recording locations in differing habitats, such as riparian woodlands and shrublands. We did not include habitat variables in our models because we expected a change in habitat to also change the bird community. If acoustic indices were effective in their purest form, they should reflect variations in bird activity, diversity, and richness regardless of community composition. We thought this to be especially true because these differing habitats were not large enough to create an auditory barrier from the more grassland-type species and could be heard amongst the woodland and shrubland species. However, many have found habitat characteristics to relate to acoustic index patterns (Do Nascimento et al. 2020; Mitchell et al. 2020; Retamosa Izaguirre et al. 2021). Considering our weaker than expected results and how acoustic indices seem to work differently among habitats (Do

Nascimento et al. 2020; Mitchell et al. 2020; Retamosa Izaguirre et al. 2021), including habitat variables in models may have improved their predictive power. Another potentially useful approach could include treating site as a “random effect” within a Generalized Linear Mixed Models framework (Dean and Nielsen 2007). However, an increase in predictor variables or model complexity would have required a larger sample size at each survey/recording location. Because we did not include any measures of biocondition or habitat quality in our models, the influence of distance to interstate may have been inflated. Habitat conditions may have improved or changed further from the source of anthropony due to reasons not associated with the interstate (e.g., a housing development existed directly across the river from the eastern portion of Mormon Island).

Conclusions

Overall, we did not find strong evidence that acoustic indices should be used as a proxy to typical avian point-count surveys in tallgrass prairies in the CPRV; this may be particularly problematic in systems with significant anthropony. However, because we found slight or weak patterns throughout our data, we hypothesize that acoustic indices may be useful if more attention to habitat, anthropony, and geophony and their effects on the soundscape are considered. This would include having measures of anthropony and geophony included in models, like we did in this study, while also including habitat classifications that would differ in baseline geophony such as woodlands, grasslands, and shrublands. Distance to habitat edge may also be worth considering because tangential habitat biodiversity may blend into the soundscape making patterns or relationships more difficult to determine. Many acoustic indices were designed to calculate sound intensity

that transfers to abundance but have still found occasional relationships with richness. Keeping in mind the nature of each specific acoustic index, we suggest using multiple measures of avian diversity such as richness and abundance collected with a limited survey radius when establishing acoustic index monitoring. If acoustic indices are going to be a tool of the future of conservation, we need to remember the context that each index was made in and how acoustic indices work in tandem with the surrounding environment.

V. TABLES

Table 1. Summary statistics for variables included in models (n=93). Standard error of the mean (SE.mean), confidence level of the mean (CL.mean), variance (var), standard deviation (std.dev), acoustic complexity index (ACI), acoustic diversity index (ADI), acoustic evenness index (AEI), bioacoustics index (BIO), acoustic entropy index (H), normalized difference sound index (NDSI), northerly wind (0 or 1, NORTH), wind speed (kph, WIND), temperature (C°, TEMP), Julian date (JD), distance to interstate (m, DIST_INTERSTATE), and distance to transect (m, DIST_TRANSECT).

Variable	Min	Max	Median	Mean	SE.mean	CL.mean	var	std.dev
ABUNDANCE_IN	7	55	20	21.6	0.9	1.9	81.0	9.0
TOTAL_ABUNDANCE	46	155	78	80.3	2.30	4.6	491.7	22.2
RICHNESS_IN	4	15	6	7.2	0.3	0.6	8.1	2.8
RICHNESS_TOTAL	7	22	14	14.5	0.4	0.9	18.0	4.2
SIMP_DIV_IN	0.59	0.92	0.79	0.79	0.01	0.01	0.01	0.07
SIMP_DIV_TOTAL	0.61	0.94	0.86	0.84	0.01	0.02	0.01	0.08
GRASS_ABUN_IN	0	49	18	18.5	1.0	2.0	91.1	9.5
GRASS_ABUN_TOTAL	9	143	67	67.8	3.3	6.5	1007.7	31.7
ACI	8,986	13,077	9,706	9,805	62.43	124.1	362,479	602.1
ADI	0.262	2.251	1.708	1.581	0.051	0.102	0.246	0.496
AEI	0.162	0.877	0.517	0.539	0.018	0.035	0.029	0.171
BIO	3.08	13.41	7.21	7.30	0.18	0.35	2.90	1.70
H	0.279	0.932	0.672	0.703	0.016	0.031	0.022	0.150
NDSI	-0.539	0.983	0.803	0.730	0.027	0.054	0.070	0.264
WIND	0	19.3	6.4	6.0	0.40	0.79	14.6	3.82
NORTH	0	1	0	0.46	0.052	0.10	0.25	0.50
TEMP	8.9	27.2	20.6	19.7	0.43	0.85	17.0	4.12
JD	145	201	175	173.8	1.8	3.5	285.0	16.9
DIST_TRANSECT	0	400	216	168.9	14.8	29.4	20,424.8	142.9
DIST_INTERSTATE	774	3,150	2,200	2,222.6	58.6	116.4	319,169.6	565.0

Table 2. Pearson's Product-Moment Correlations between outcome variables such as avian abundance within 50 m (ABUNDANCE_IN), total avian abundance (TOTAL_ABUNDANCE), avian richness within 50 m (RICHNESS_IN), total avian richness (RICHNESS_TOTAL), avian Simpson diversity index within 50 m (SIMP_DIV_IN), total avian Simpson diversity (SIMP_DIV_TOTAL), avian grassland species abundance within 50 m (GRASS_ABUN_IN), and total avian grassland species abundance (GRASS_ABUN_TOTAL) and acoustic indices such as acoustic complexity index (ACI), acoustic diversity index (ADI), acoustic evenness index (AEI), bioacoustics index (BIO), acoustic entropy index (H), and normalized difference sound index (NDSI). Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

	ACI	ADI	AEI	BIO	H	NDSI
ABUNDANCE_IN	0.104	0.283**	-0.232*	0.044	0.220*	-0.011
TOTAL_ABUNDANCE	0.149	0.325**	-0.282**	-0.135	0.250*	0.015
RICHNESS_IN	-0.194.	0.146	-0.118	0.028	-0.023	0.004
RICHNESS_TOTAL	-0.256*	0.027	-0.030	-0.203.	-0.101	-0.123
SIMP_DIV_IN	-0.118	0.146	-0.155	0.033	0.027	-0.106
SIMP_DIV_TOTAL	-0.172.	0.029	-0.069	-0.048	-0.046	-0.130
GRASS_ABUN_IN	0.245*	0.251*	-0.231*	0.265*	0.156	0.117
GRASS_ABUN_TOTAL	0.206*	0.174.	-0.163	0.195.	0.151	0.136

Table 3. Pearson correlations between acoustic indices such as acoustic complexity index (ACI), acoustic diversity index (ADI), acoustic evenness index (AEI), bioacoustics index (BIO), acoustic entropy index (H), and normalized difference sound index (NDSI). Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

	ACI	ADI	AEI	BIO	H
ADI	0.360***				
AEI	-0.396***	-0.942***			
BIO	0.057	0.163	-0.035		
H	0.243**	0.677***	-0.690***	-0.065	
NDSI	0.056	0.335**	-0.304**	0.362***	0.194.

Table 4. Pearson correlations between avian community outcome variables such as avian abundance within 50 m (ABUNDANCE_IN), total avian abundance (TOTAL_ABUNDANCE), avian richness within 50 m (RICHNESS_IN), total avian richness (RICHNESS_TOTAL), avian Simpson diversity index within 50 m (SIMP_DIV_IN), total avian Simpson diversity (SIMP_DIV_TOTAL), avian grassland species abundance within 50 m (GRASS_ABUN_IN), and total avian grassland species abundance (GRASS_ABUN_TOTAL) and environmental and temporal predictor variables such as Julian date (JD), northerly wind (0 or 1, NORTH), wind speed (kph, WIND), temperature (C°, TEMP), distance to interstate (m, DIST_INTERSTATE), and distance to transect (m, DIST_TRANSECT). Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

	JD	NORTH	WIND	TEMP	DIST INTERSTATE	DIST TRANSECT
ABUNDANCE IN	-0.062	-0.015	-0.274**	0.044	0.143	-0.043
TOTAL ABUNDANCE	-0.002	-0.035	-0.140	0.076	-0.090	0.182.
RICHNESS IN	0.138	-0.133	-0.169	0.080	0.575***	-0.176.
RICHNESS TOTAL	0.212*	-0.229*	-0.017	0.205*	0.266**	-0.057
SIMP_DIV IN	0.078	-0.045	-0.187.	0.089	0.552***	-0.051
SIMP_DIV TOTAL	0.168	-0.199.	-0.092	0.214*	0.398***	0.010
GRASS_ABUN IN	-0.238*	0.047	-0.159	-0.046	-0.278**	0.049
GRASS_ABUN TOTAL	-0.177.	0.138	-0.083	-0.141	-0.301**	0.116

Table 5. Pearson correlations between environmental and temporal predictor variables such as Julian date (JD), northerly wind (0 or 1, NORTH), wind speed (kph, WIND), temperature (C°, TEMP), distance to interstate (m, DIST_INTERSTATE), and distance to transect (m, DIST_TRANSECT) and acoustic indices such as acoustic complexity index (ACI), acoustic diversity index (ADI), acoustic evenness index (AEI), bioacoustics index (BIO), acoustic entropy index (H), and normalized difference sound index (NDSI). Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

	ACI	ADI	AEI	BIO	H	NDSI
JD	-0.354***	-0.132	0.0926	-0.216*	-0.201.	0.0261
NORTH	-0.0309	0.126	-0.108	0.0541	0.210*	-0.200.
WIND	0.112	-0.306**	0.319**	-0.115	-0.116	-0.152
TEMP	-0.0612	-0.0931	-0.0176	-0.222*	-0.0239	0.218*
DIST_INTERSTATE	-0.410***	-0.114	0.133	0.0643	-0.195.	0.139
DIST_TRANSECT	-0.0439	0.0991	-0.0521	0.126	0.289**	0.146

Table 6. Each outcome variable and the average McFadden's Psuedo-R² for the confidence set of each outcome variable. Good fit to the data is expressed as Psuedo-R² between 0.2-0.4. *best between in and total model sets.

Avian community metric	McFadden's Psuedo-R²
Richness in*	0.0924
Richness total	0.0830
Abundance in*	0.0583
Abundance total	0.0486
Simpson diversity in	-0.253
Simpson diversity total*	-0.181
Grassland species abundance in*	0.0815
Grassland species abundance total	0.0555

Table 7. Models included in the confidence set for avian richness. All models controlled for distance to transect, observer bias, and Song meter model. Cumulative weight (Cum. Wt), Log-Likelihood (LL), acoustic diversity index (ADI), distance to interstate (m, DIST_INTERSTATE), and acoustic evenness index (AEI).

Model	Variables	AICc	Delta	Weight	Cum. Wt	LL	Psuedo-R ²
		AICc					
Richness in 1	ADI + DIST_INTERSTATE	415.25	0	0.41	0.41	-201.14	0.0953
Richness in 2	AEI + DIST_INTERSTATE	415.69	0.44	0.33	0.74	-201.36	0.0943
Richness in 3	DIST_INTERSTATE	416.33	1.08	0.24	0.98	-202.82	0.0877

Table 8. Full model average variables included in confidence set for avian richness within 50 m. Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1. Standard error (SE), acoustic diversity index (ADI), acoustic evenness index (AEI), distance to interstate (m, DIST_INTERSTATE).

Coefficient	Estimate	SE	z	p
(Intercept)	9.963e-01	2.909E-01	3.398	0.0007***
ADI	6.462e-02	9.376e-02	0.686	0.493
AEI	-1.350e-01	2.335e-01	0.575	0.565
DIST_INTERSTATE	3.953e-04	7.104e-05	5.488	<0.0001***

Table 9. Models included in the confidence set for avian abundance. All models controlled for distance to transect, observer bias, and Song meter model. Cumulative weight (Cum. Wt), Log-Likelihood (LL), acoustic evenness index (AEI), distance to interstate (m, DIST_INTERSTATE), acoustic complexity index (ACI), normalized difference sound index (NDSI), wind speed (kph, WIND), acoustic entropy index (H), time of survey (TIME), bioacoustics index (BIO), acoustic diversity index (ADI), Julian date (JD), and northerly wind (0 or 1, NORTH).

Model	Variables	AICc	Delta AICc	Weight	Cum. Wt	LL	Psuedo-R ²
Abundance in 1	AEI*DIST_INTERSTATE + ACI*DIST_INTERSTATE + NDSI*WIND	639.24	0	0.58	0.58	-304.32	0.0631
Abundance in 2	H + TIME + NDSI*DIST_INTERSTATE + BIO*WIND + ACI*WIND + NDSI*WIND	641.16	1.91	0.22	0.81	-301.00	0.0733
Abundance in 3	H	642.75	3.51	0.10	0.91	-314.89	0.0305
Abundance in 4	ADI + TIME + NDSI*DIST_INTERSTATE + BIO*WIND + ACI*WIND + NDSI*WIND	645.15	5.91	0.03	0.94	-303.00	0.0671
Abundance in 5	BIO + H + ACI + NDSI + WIND + TIME + JD + NORTH + DIST_INTERSTATE	645.93	6.69	0.02	0.96	-306.27	0.0570

Table 10. Full model average variables included in confidence set for avian abundance within 50 m. Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1. Standard error (SE), acoustic evenness index (AEI), acoustic complexity index (ACI), normalized difference sound index (NDSI), acoustic entropy index (H), bioacoustics index (BIO), acoustic diversity index (ADI), distance to interstate (m, DIST_INTERSTATE), wind speed (kph, WIND), time of survey (TIME), Julian date (JD), and northerly wind (0 or 1, NORTH).

Coefficient	Estimate	SE	z	p
(Intercept)	-1.665e+04	3.070e+04	0.540	0.589
AEI	1.942e+00	1.742e+00	1.111	0.267
ACI	4.699e-04	5.034e-04	0.931	0.352
NDSI	-7.920e-01	6.187e-01	1.273	0.203
H	3.325e-01	4.791e-01	0.693	0.489
BIO	2.237e-02	4.235e-02	0.526	0.599
ADI	6.230e-03	3.785e-02	0.164	0.870
AEI:DIST_INTERSTATE	-1.014e-03	8.838e-04	1.145	0.252
ACI:DIST_INTERSTATE	-2.102e-07	1.959e-07	1.069	0.285
NDSI:DIST_INTERSTATE	9.944e-05	1.901e-04	0.521	0.602
NDSI:WIND	1.065e-01	6.804e-02	1.552	0.121
BIO:WIND	-5.345e-03	1.006e-02	0.529	0.597
ACI:WIND	1.623e-05	3.011e-05	0.537	0.591
DIST_INTERSTATE	2.630e-03	2.412e-03	1.087	0.277
WIND	-2.346e-01	2.656e-01	0.880	0.379
TIME	-7.538e-06	1.390e-05	0.540	0.589
JD	-2.553e-05	3.806e-04	0.066	0.947
NORTH	-1.300e-03	1.468e-02	0.088	0.930

Table 11. Models included in the confidence set for avian Simpson diversity. All models controlled for distance to transect, observer bias, and Song meter model. Cumulative weight (Cum. Wt), Log-Likelihood (LL), Julian date (JD), acoustic diversity index (ADI), distance to interstate (m, DIST_INTERSTATE), normalized difference sound index (NDSI), acoustic evenness index (AEI), time of survey (TIME), and northerly wind (0 or 1, NORTH).

Model	Variables	AICc	Delta AICc	Weight	Cum. Wt	LL	Psuedo- R ²
SDI total 1	JD + ADI*DIST_INTERSTATE + NDSI*DIST_INTERSTATE	-225.66	0	0.54	0.54	125.46	-0.176
SDI total 2	AEI + TIME + JD + NORTH + NDSI*DIST_INTERSTATE	-225.23	0.43	0.43	0.97	126.56	-0.187

Table 12. Full model average variables included in confidence set for total avian Simpson diversity. Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1. Standard error (SE), acoustic diversity index (ADI), normalized difference sound index (NDSI), acoustic evenness index (AEI), distance to interstate (m, DIST_INTERSTATE), Julian date (JD), time of survey (TIME), and northerly wind (0 or 1, NORTH).

Coefficient	Estimate	SE	z	p
(Intercept)	-6.729e+03	9.478e+03	0.706	0.480
ADI	-1.475e-01	1.523e-01	0.965	0.334
NDSI	4.341e-01	1.201e-01	3.571	0.000356***
AEI	7.786e-02	9.592e-02	0.809	0.418
ADI:DIST_INTERSTATE	5.592e-05	5.990e-05	0.929	0.353
NDSI:DIST_INTERSTATE	-1.440e-04	5.516e-05	2.584	0.00976**
DIST_INTERSTATE	-8.358e-05	8.463e-05	0.982	0.326
JD	-1.256e-03	5.901e-04	2.098	0.0359*
TIME	-3.047e-06	4.290e-06	0.706	0.480
NORTH	1.784e-02	2.435e-02	0.729	0.466

Table 13. Models included in the confidence set for avian grassland species abundance. All models controlled for distance to transect, observer bias, and Song meter model. Cumulative weight (Cum. Wt), Log-Likelihood (LL), wind speed (kph, WIND), Julian date (JD), acoustic complexity index (ACI), distance to interstate (m, DIST_INTERSTATE), and normalized difference sound index (NDSI).

Model	Variables	AICc	Delta AICc	Weight	Cum. Wt	LL	Pseudo-R ²
Grassland species abundance 1	WIND + JD + ACI*DIST_INTERSTATE + NDSI*DIST_INTERSTATE	6754.80	0	0.98	0.98	-313.45	0.0815

Table 14. Full model average variables included in confidence set for avian grassland species abundance within 50 m. Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1. Standard error (SE), acoustic complexity index (ACI), normalized difference sound index (NDSI), distance to interstate (m, DIST_INTERSTATE), wind speed (kph, WIND), and Julian date (JD).

Coefficient	Estimate	SE	z	p
(Intercept)	2.525e+02	6.619e+01	3.758	0.000171***
ACI	-2.121e-02	6.724e-03	3.108	0.00189**
NDSI	3.407e+01	9.593e+00	3.499	0.000467***
ACI:DIST_INTERSTATE	9.965e-06	3.060e-06	3.209	0.00133**
NDSI:DIST_INTERSTATE	-1.264e-02	3.986e-03	3.124	0.00178**
DIST_INTERSTATE	-9.401e-02	2.935e-02	3.155	0.00160**
WIND	-6.950e-01	3.494e-01	1.959	0.0501.
JD	-1.654e-01	5.230e-02	3.116	0.00183**

VI. FIGURES

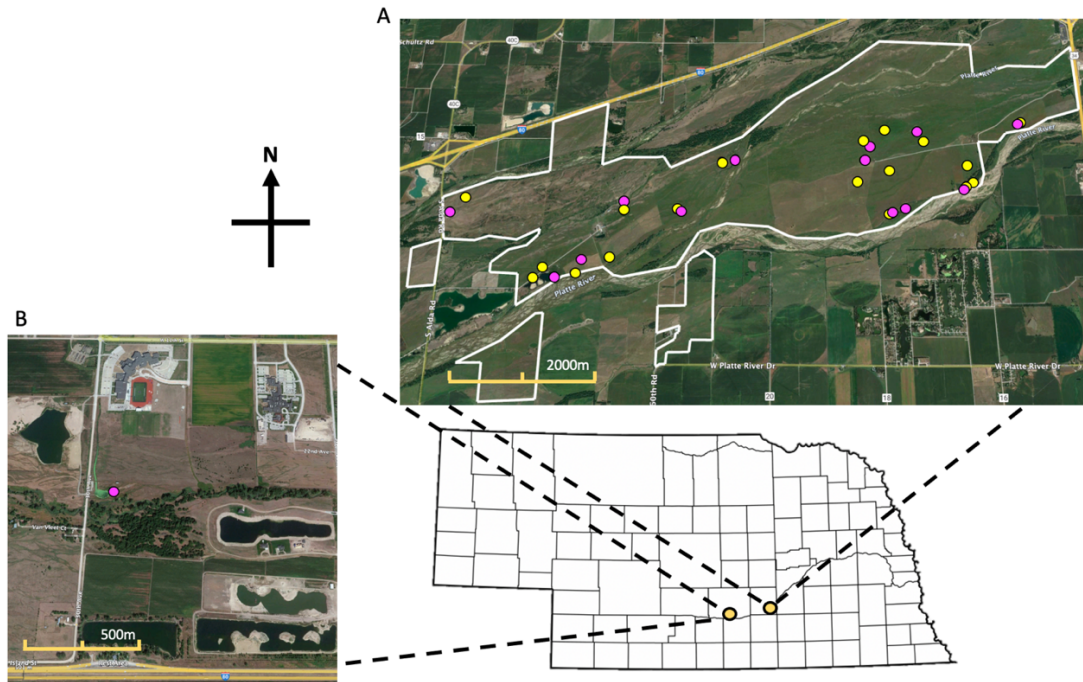


Figure 1. Acoustic recorder locations (pink) and monitoring plots (yellow) on Shoemaker Island and Mormon Island of the Platte River near Grand Island, NE (A). Acoustic recorder location west of Crane Trust property near the north channel of the Platte River in Kearney, NE, at the Kearney Outdoor Learning Area (B).

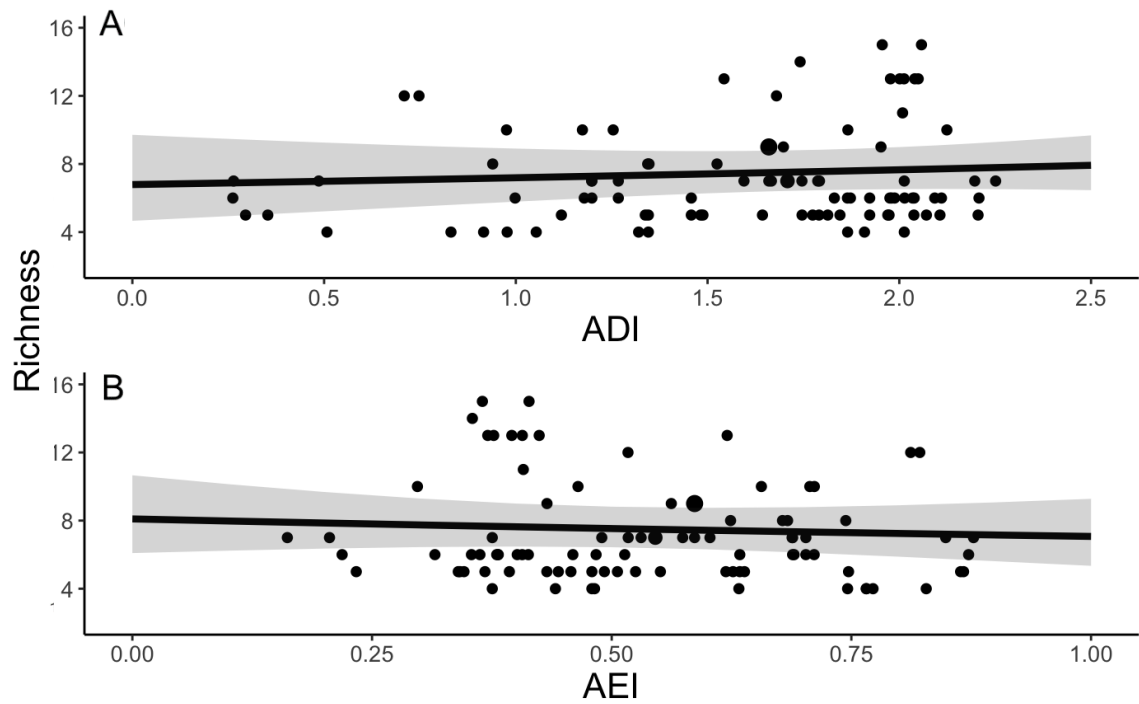


Figure 2. Model averaged acoustic indices relationship to richness for ADI (A) and AEI (B) included in model confidence set for avian richness with a limited survey radius. Grey area indicates 95% confidence intervals

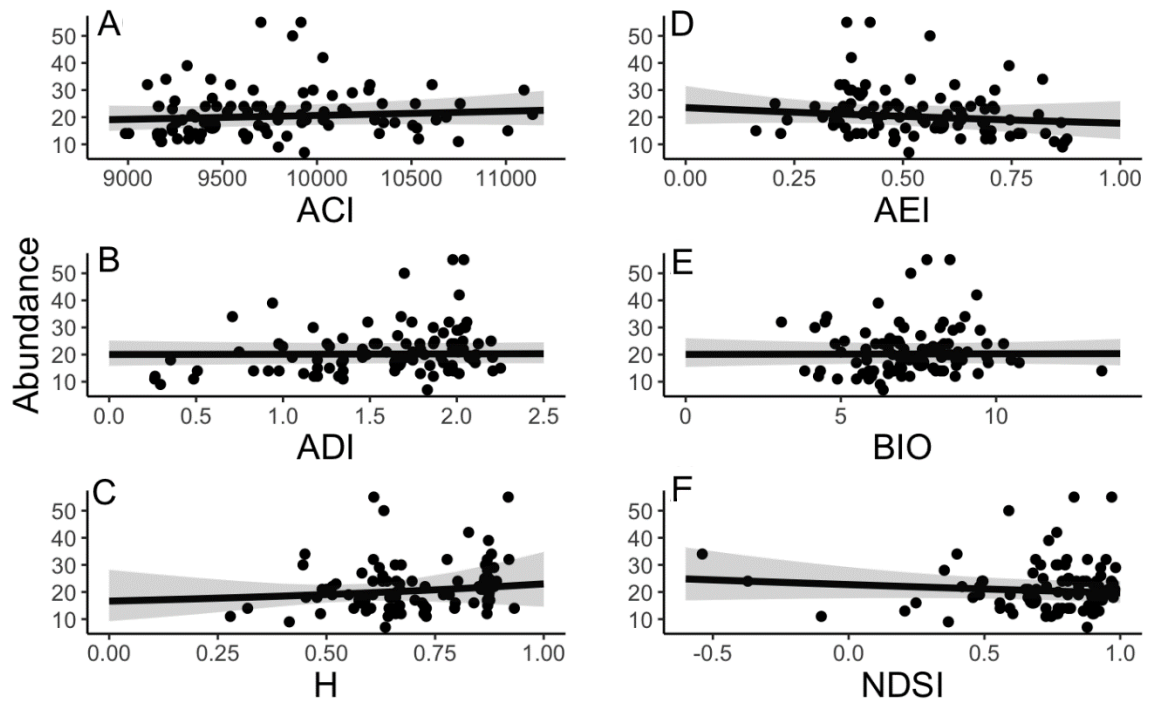


Figure 3. Model averaged acoustic indices relationship to abundance for ACI (A), ADI (B), H (C), AEI (D), BIO (E), and NDSI (F) included in model confidence set for avian abundance with a limited survey radius. Grey area indicates 95% confidence intervals.

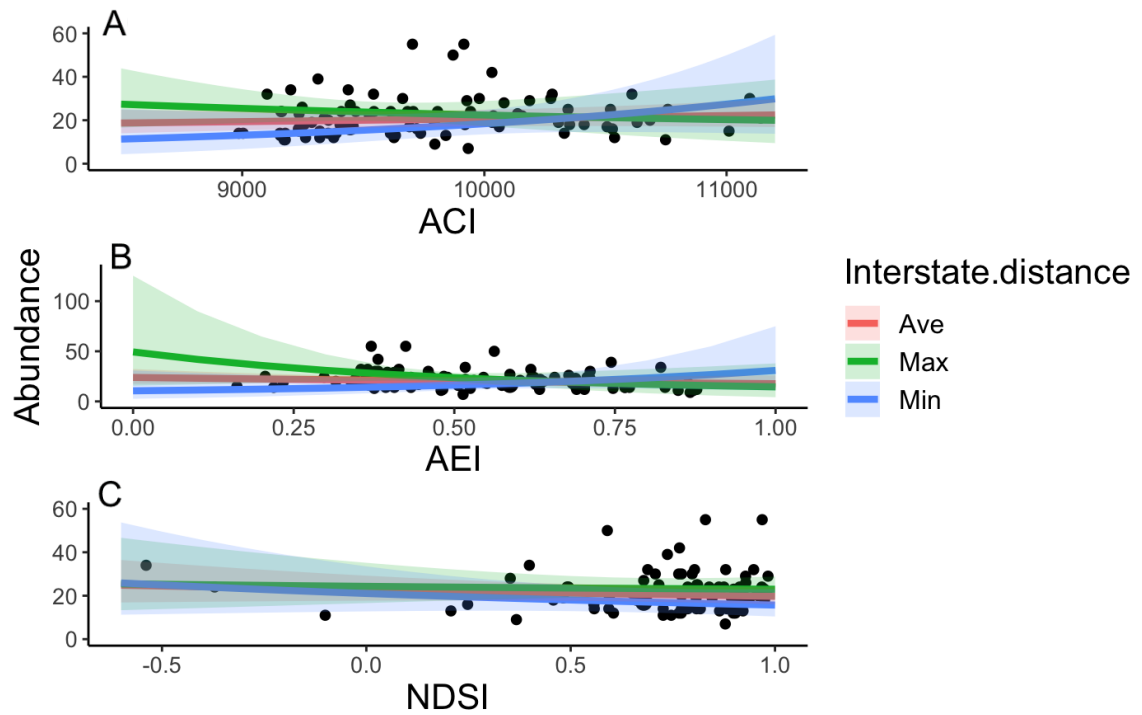


Figure 4. Model averaged acoustic indices relationship to abundance for ACI (A), AEI (B), and NDSI (C) when considering maximum (green), mean (red), and minimum (blue) distances (m) away from the interstate which was the closest major source of anthropophony to the study area. Acoustic indices shown were in model confidence set for avian abundance with a limited survey radius.

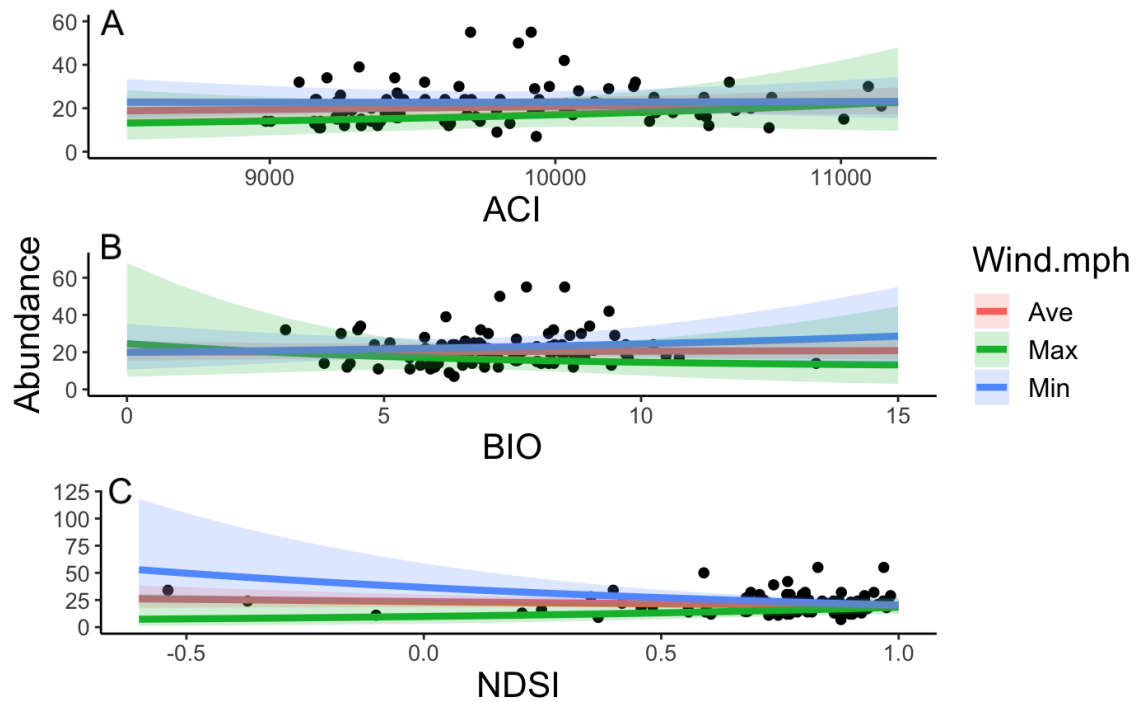


Figure 5. Model averaged acoustic indices relationship to abundance for ACI (A), BIO (B), and NDSI (C) when considering maximum (green), mean (red), and minimum (blue) wind speeds during surveys. Acoustic indices shown were in model confidence set for avian abundance with a limited survey radius.

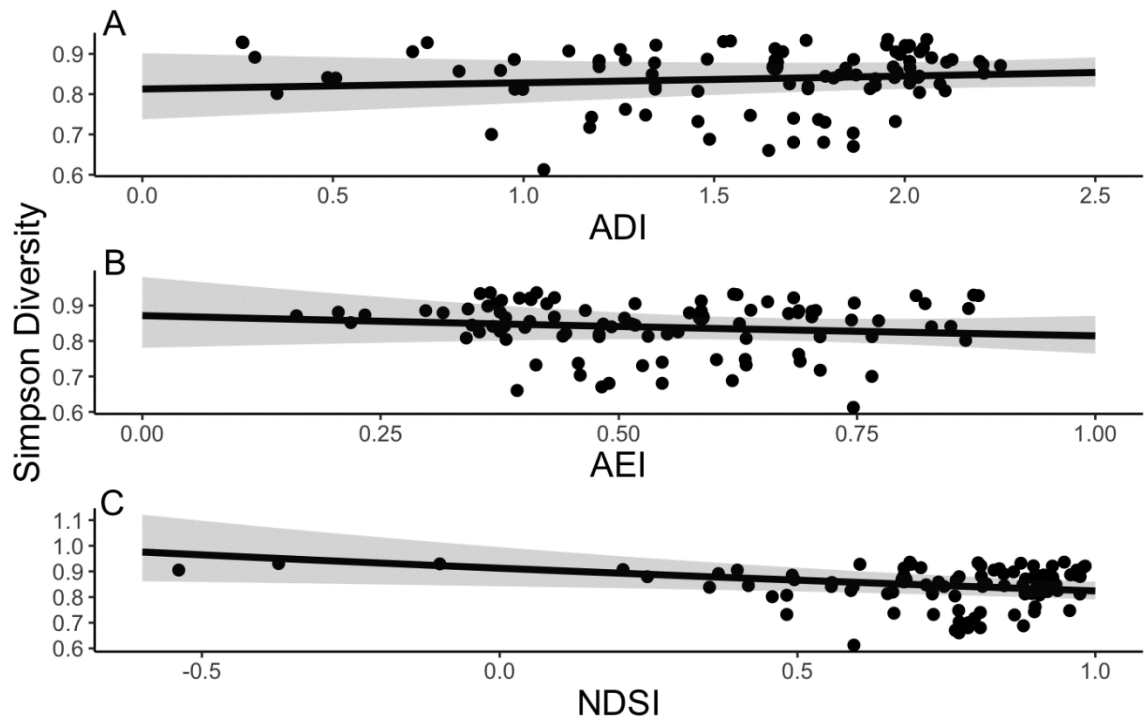


Figure 6. Model averaged acoustic indices relationship to Simpson diversity for ACI (A), AEI (B), and NDSI (C) included in model confidence set for avian Simpson diversity with an unlimited survey radius. Grey area indicates 95% confidence intervals.

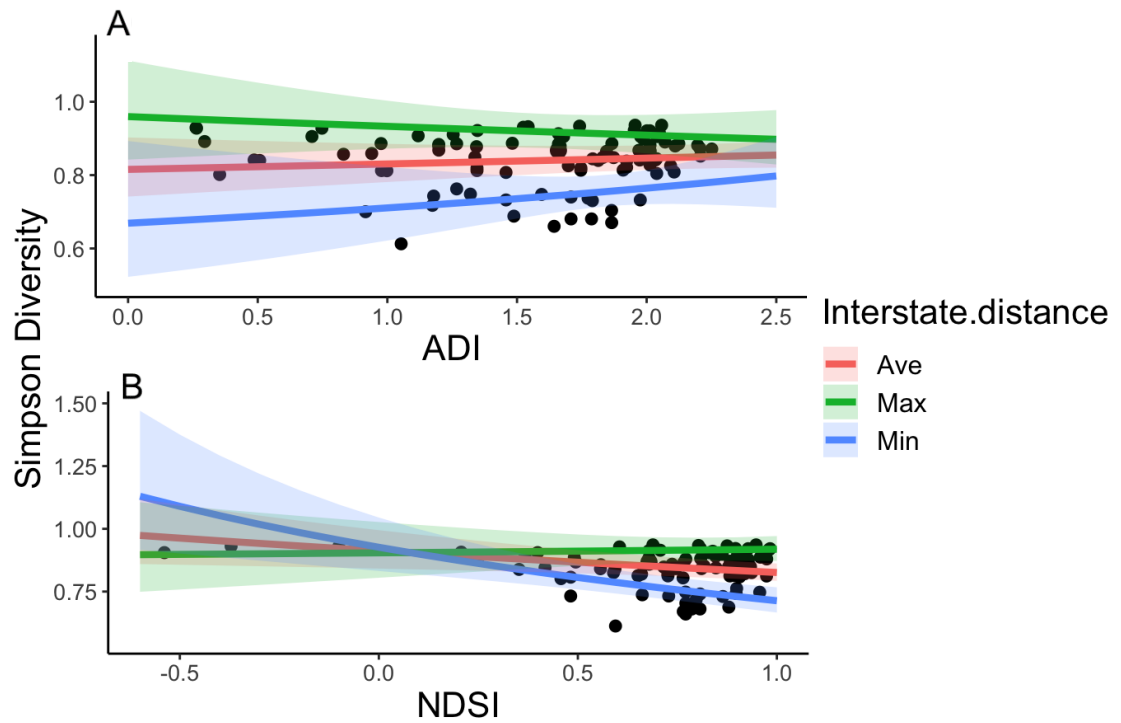


Figure 7. Model averaged acoustic indices relationship to Simpson diversity for ADI (A) and NDSI (B) when considering maximum (green), mean (red), and minimum (blue) distances (m) away from the interstate which was the closest major source of anthropophony to the study area. Acoustic indices shown were in model confidence set for avian Simpson diversity with an unlimited survey radius.

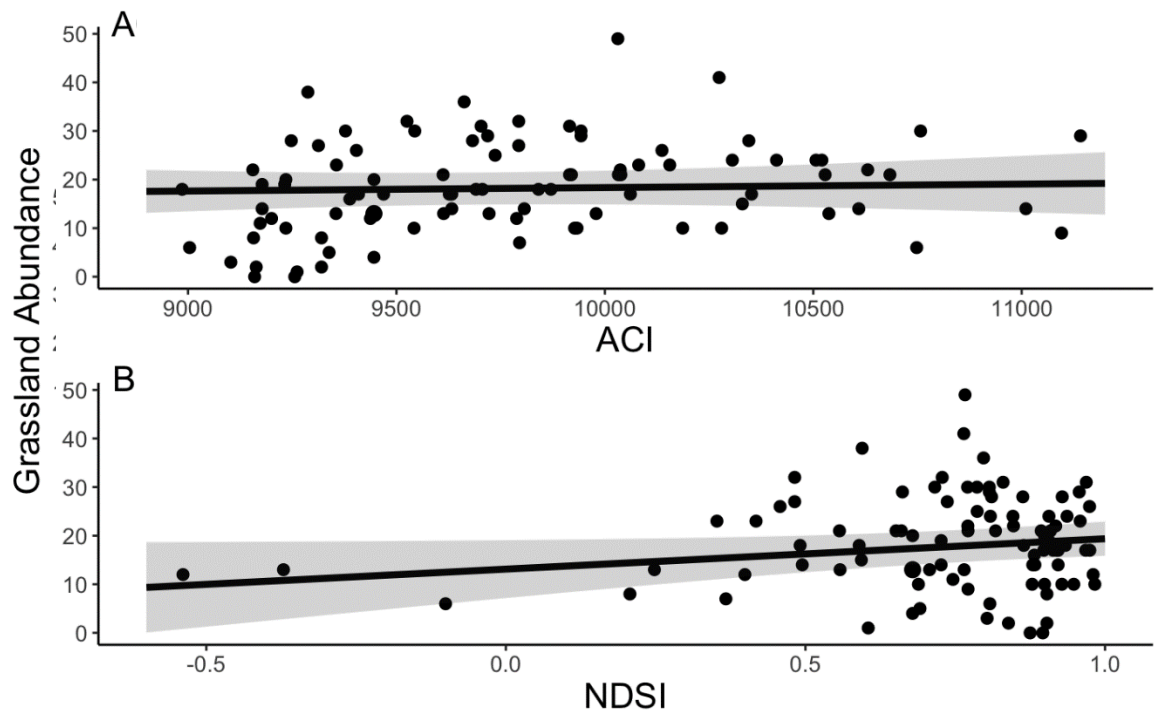


Figure 8. Model averaged acoustic indices relationship to grassland species abundance for ACI (A) and NDSI (B) included in model confidence set for avian grassland species abundance with a limited survey radius. Grey area indicates 95% confidence intervals.

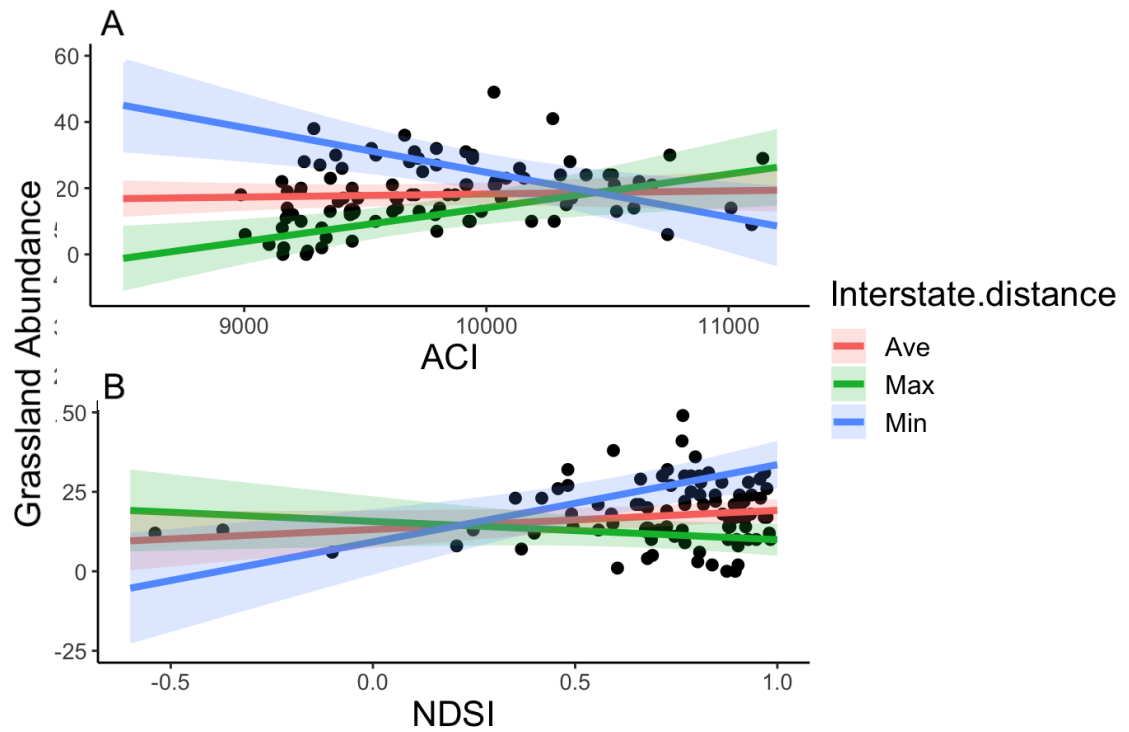


Figure 9. Model averaged acoustic indices relationships to grassland species abundance for ACI (A) and NDSI (B) when considering maximum (green), mean (red), and minimum (blue) distances (m) from the interstate, which was the closest major source of anthropophony to the study area. Acoustic indices shown were in model confidence set for avian grassland species abundance with a limited survey radius.

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VII. APPENDIX

Appendix A. List of species recorded on avian point count surveys within a 50 m radius (Count In), outside a 50 m radius (Count Out), and the total counts of each during the breeding seasons of 2019, 2020, and 2021 in the Central Platte River Valley, NE, at each monitoring plot paired with an audio recorder.

Common Name	Scientific Name	Count In	Count Out	Total Count
American Crow	<i>Corvus brachyrhynchos</i>	0	1	1
American Goldfinch	<i>Spinus tristis</i>	91	106	197
American Kestrel	<i>Falco sparverius</i>	0	1	1
American Robin	<i>Turdus migratorius</i>	36	146	182
Baird's Sandpiper	<i>Calidris bairdii</i>	0	15	15
Bald Eagle	<i>Haliaeetus leucocephalus</i>	1	28	29
Baltimore Oriole	<i>Icterus galbula</i>	3	48	51
Bank Swallow	<i>Riparia riparia</i>	2	5	7
Barn Swallow	<i>Hirundo rustica</i>	42	52	94
Bell's Vireo	<i>Vireo bellii</i>	13	17	30
Belted Kingfisher	<i>Megaceryle alcyon</i>	0	4	4
Blue Jay	<i>Cyanocitta cristata</i>	3	35	38
Blue-winged Teal	<i>Anas discors</i>	1	0	1
Bobolink	<i>Dolichonyx oryzivorus</i>	242	484	726
Brown Thrasher	<i>Toxostoma rufum</i>	12	21	33
Brown-headed Cowbird	<i>Molothrus ater</i>	438	847	1285
Canada Goose	<i>Branta canadensis</i>	0	141	141
Cattle Egret	<i>Bubulcus ibis</i>	11	0	11
Cliff Swallow	<i>Petrochelidon pyrrhonota</i>	125	270	395
Common Grackle	<i>Quiscalus quiscula</i>	6	25	31
Common Yellowthroat	<i>Geothlypis trichas</i>	65	241	306
Dickcissel	<i>Spiza americana</i>	281	712	993
Downy Woodpecker	<i>Picoides pubescens</i>	1	2	3
Eastern Kingbird	<i>Tyrannus tyrannus</i>	24	52	76
Eastern Meadowlark	<i>Sturnella magna</i>	14	46	60
Eastern Wood-Pewee	<i>Contopus virens</i>	0	3	3
Eurasian Collared- Dove	<i>Streptopelia decaocto</i>	2	2	4
European Starling	<i>Sturnus vulgaris</i>	37	61	98
Field Sparrow	<i>Spizella pusilla</i>	0	15	15

Grasshopper Sparrow	<i>Ammodramus</i>	66	79	145
	<i>savannarum</i>			
Gray Catbird	<i>Dumetella carolinensis</i>	14	8	22
Great Blue Heron	<i>Ardea herodias</i>	0	6	6
Great Crested Flycatcher	<i>Myiarchus crinitus</i>	0	2	2
Great Egret	<i>Ardea alba</i>	1	0	1
Greater Prairie- Chicken	<i>Tympanuchus cupido</i>	0	11	11
House Finch	<i>Haemorhous mexicanus</i>	2	0	2
House Sparrow	<i>Passer domesticus</i>	3	1	4
House Wren	<i>Troglodytes aedon</i>	22	81	103
Killdeer	<i>Charadrius vociferus</i>	30	201	231
Mallard	<i>Anas platyrhynchos</i>	3	36	39
Marsh Wren	<i>Cistothorus palustris</i>	0	1	1
Mourning Dove	<i>Zenaida macroura</i>	35	142	177
Northern Bobwhite	<i>Colinus virginianus</i>	5	153	158
Northern Cardinal	<i>Cardinalis cardinalis</i>	5	17	22
Northern Flicker	<i>Colaptes auratus</i>	1	17	18
Orchard Oriole	<i>Icterus spurius</i>	29	64	93
Red-bellied Woodpecker	<i>Melanerpes carolinus</i>	0	6	6
Red-eyed Vireo	<i>Vireo olivaceus</i>	0	1	1
Red-headed Woodpecker	<i>Melanerpes</i> <i>erythrocephalus</i>	1	30	31
Red-tailed Hawk	<i>Buteo jamaicensis</i>	0	5	5
Red-winged Blackbird	<i>Agelaius phoeniceus</i>	569	2023	2592
Ring-necked Pheasant	<i>Phasianus colchicus</i>	4	151	155
Rock Pigeon	<i>Columba livia</i>	0	33	33
Rose-breasted Grosbeak	<i>Pheucticus ludovicianus</i>	0	1	1
Sedge Wren	<i>Cistothorus platensis</i>	7	27	34
Song Sparrow	<i>Melospiza melodia</i>	43	166	209
Sora	<i>Porzana carolina</i>	0	1	1
Spotted Sandpiper	<i>Actitis macularius</i>	5	19	24
Spotted Towhee	<i>Pipilo maculatus</i>	0	6	6
Swamp Sparrow	<i>Melospiza georgiana</i>	3	41	44
Tree Swallow	<i>Tachycineta bicolor</i>	30	30	60
Turkey Vulture	<i>Cathartes aura</i>	1	2	3
Upland Sandpiper	<i>Bartramia longicauda</i>	1	19	20

Warbling Vireo	<i>Vireo gilvus</i>	3	24	27
Western Meadowlark	<i>Sturnella neglecta</i>	124	436	560
White-breasted Nuthatch	<i>Sitta carolinensis</i>	0	1	1
White-rumped Sandpiper	<i>Calidris fuscicollis</i>	0	2	2
Wild Turkey	<i>Meleagris gallopavo</i>	0	1	1
Willow Flycatcher	<i>Empidonax traillii</i>	28	60	88
Wilson's Phalarope	<i>Phalaropus tricolor</i>	17	16	33
Wilson's Snipe	<i>Gallinago delicata</i>	3	13	16
Yellow Warbler	<i>Setophaga petechia</i>	70	167	237
Yellow-shafted Flicker	<i>Colaptes a. auratus</i>	0	2	2