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RESEARCH ARTICLE

Application of passive acoustic monitoring to compare avian populations in perennial grasslands and croplands in Nebraska

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Abstract

1. Perennial grasses, such as switchgrass (*Panicum virgatum*), have emerged as a promising and reliable feedstock for bioenergy production, offering a potential alternative to conventional feedstocks (e.g. corn). Incorporating perennial grasses into agroecosystems can also enhance biodiversity across multiple taxa, including providing crucial habitat to declining grassland bird populations. Understanding the habitat value of different bioenergy crops in relation to the surrounding landscape will require extensive data to assess the trade-offs between bioenergy production and supporting grassland bird populations.
2. We used passive acoustic monitoring (PAM) to compare bird communities in perennial grasslands and croplands in southwestern Nebraska.
3. Species richness for grassland-obligate species and species of conservation need (SCN) were consistently higher in grasslands than cornfields throughout most of the monitoring period spanning from March to September. Additionally, we found that the amount of grassland habitat around monitoring locations significantly influenced the effectiveness of field types in supporting avian populations. We found that PAM provided a more robust and detailed account of avian occupancy of perennial grasslands and croplands compared to point count surveys, but several limitations must be considered before the widespread application of this technology to answer ecological research questions.
4. *Practical Implication*. Incorporating perennial grasslands into agroecosystems can not only provide an additional source of bioenergy feedstock but also support declining avian populations, contributing to the development and sustainability of the bioeconomy.

KEYWORDS
bioeconomy, bioenergy, grassland birds, ornithology, passive acoustic monitoring, perennial grasslands, switchgrass

1 | INTRODUCTION

Transitioning to a bioeconomy, where renewable biological resources replace fossil fuels in the production of energy and other goods, is increasingly important due to risks associated with climate change and the pressures of a growing global population (Pascoli et al., 2022). Corn (*Zea mays*), the predominant feedstock used for ethanol biofuel in the United States, is grown on approximately 12 million acres of US croplands (Long et al., 2015; Sturchio et al., 2025). Feedstock refers to the raw biomass resources, such as specific plant sources, that are used for bioenergy conversion (Long et al., 2015; Pascoli et al., 2022). Despite its bioenergy potential, corn ethanol remains controversial due to concerns over its net energy production (Tilman et al., 2009), water consumption (Wu et al., 2009), effectiveness in reducing greenhouse gas emissions (Scully et al., 2021) and competition with food production (Koizumi, 2015). Perennial grasses, such as switchgrass (*Panicum virgatum*), have been recognized as a reliable feedstock capable of replacing corn on marginal lands to help meet annual renewable fuel targets (Mitchell et al., 2012, 2016). Conversion of row-crop fields to perennial grasslands dedicated to bioenergy can also promote biodiversity and ecological benefits (Fletcher Jr et al., 2011). However, the extent to which the cultivation of bioenergy grasslands can align with conservation goals in agricultural landscapes is not yet fully understood.

The loss of temperate grasslands has been mainly driven by the expansion of row-crop agriculture (Hoekstra et al., 2005), which has had cascading effects on grassland-dependent species, specifically grassland bird populations. Since the 1970s, grassland bird populations have experienced significant declines (Rosenberg et al., 2019). Previous studies have indicated that perennial grassland fields could provide critical habitat for birds, both on breeding grounds (Blank et al., 2014) and at migratory stopover sites (Robertson et al., 2011) while simultaneously serving as effective bioenergy feedstocks. Bioenergy grasslands, such as switchgrass, are typically harvested once per year, after the avian nesting season, thereby minimizing disturbances to grassland breeding birds (Roth et al., 2005). Beyond the timing of harvest, the spatial arrangement of these bioenergy grasslands is a major factor. Strategic placement of bioenergy grasslands affects the ability of producers to deliver biomass to a biomass-processing plant in a timely manner (Mitchell et al., 2012) and also contributes to the creation of larger patches of grassland habitat. This can benefit area-sensitive bird species that rely on extensive grassland coverage (Robertson et al., 2012). Comparing the habitat value of different potential bioenergy crops in relation to the grassland habitat in the surrounding landscape will require long-term, detailed data to assess the trade-offs between bioenergy production and supporting declining grassland bird populations.

Production of monoculture grassland feedstocks (e.g. switchgrass) is fairly uncommon in the Midwest (Robertson et al., 2013). Therefore, previous research examining bioenergy grassland's ability to support avian populations has often relied on available perennial grasslands, which are not always representative of monoculture bioenergy crops. Some studies included multiple switchgrass fields in their study sites (Blank et al., 2014; Robertson et al., 2011), while others examined perennial grasslands where switchgrass was the dominant species, though not planted as a pure switchgrass monoculture (Murray et al., 2003; Robertson et al., 2013; Roth et al., 2005). Perennial grasslands enrolled in the Conservation Reserve Program (CRP) or managed for other conservation purposes are commonly used as surrogates for bioenergy grasslands in many research efforts (Blank et al., 2014; Murray et al., 2003; Robertson et al., 2011, 2013; Roth et al., 2005). This may stem from the interest in converting land currently enrolled in CRP to perennial energy crops, which could reduce rental payments, lower overall program costs, increase economic returns for landowners and mitigate GHG emissions (Chen et al., 2021). Drawing conclusions about the impacts of bioenergy grasslands on bird populations using only non-monoculture systems may fail to fully represent future landscapes that include monoculture bioenergy crops. However, until switchgrass or other bioenergy grasslands become more widely established in the Midwest, inferences about its potential to benefit grassland birds must rely on studies of other available perennial grasslands.

The application of passive acoustic monitoring (PAM) in terrestrial ecosystems has rapidly increased over the last few decades (Sugai et al., 2019). PAM utilizes autonomous recording units (ARUs) to continuously monitor the vocalization of animals over extended periods of time (Kahl et al., 2021). This novel method offers several advantages over traditional methods (i.e. point count surveys): PAM is less labor and resource intensive (Sugai et al., 2019), provides a permanent dataset with higher temporal resolution (Ross et al., 2023) and minimizes human disturbance or biases (Gibb et al., 2019; Shonfield & Bayne, 2017). Acoustic monitoring generates vast amounts of data, driving the growing adoption of automated methods to handle large datasets in ecological research. As a result, automated classifiers for analysing large datasets are often used in conjunction with manual techniques (e.g. listening and spectrogram visualization) to enhance the likelihood of detecting a greater number of species in recordings (Ware et al., 2023). One such classifier, BirdNET, is a convolutional neural network capable of identifying over 6000 species and quickly gaining prominence in both ecology and ornithology (Wood & Kahl, 2024). BirdNET recognizes bird vocalizations from acoustic recordings by segmenting acoustic files into 3 s (s) intervals and providing a quantitative confidence score for each identification, with confidence scores ranging from 0 to 1, allowing the output to be filtered based on a selected confidence threshold (Pérez-Granados, 2023). BirdNET's confidence scores are unitless measures reflecting the model's estimated certainty in its species-level identifications (Wood & Kahl, 2024). BirdNET has been applied in several recent avian field studies, enabling the extraction of novel ecological insights on avian community and species-specific responses to landscape changes (Cole et al., 2022; Hack et al., 2024; LaGory et al., 2024). Furthermore, PAM approaches with automatic species classifiers such as BirdNET have been demonstrated to be comparable to traditional point count surveys, offering similar levels of accuracy in monitoring grassland bird populations (Schuster et al., 2024).

Although the viability of perennial grasslands as avian habitat compared to row-crop agriculture has been previously explored using traditional methods (Blank et al., 2014, 2016; Robertson et al., 2011; Roth et al., 2005), it has not yet been evaluated using modern ecological techniques, such as PAM. Previously, PAM has been used to understand whether switchgrass cultivars could serve as suitable habitat for avian species, though this approach has only been applied to small-scale bioenergy research plots (LaGory et al., 2024). In this study, we developed a PAM approach to compare bird communities in perennial grasslands and croplands in southwestern Nebraska. Our specific objectives were to:

1. Compare the richness of focal species, grassland obligates, habitat generalists and species of conservation need between perennial grasslands and croplands.
2. Examine the impact of grassland habitat in the surrounding landscape on the composition of avian communities.
3. Evaluate the effectiveness of PAM in assessing the suitability of perennial grasslands as avian habitat.

We hypothesized that grassland obligate species richness will be greater in perennial grasslands compared to croplands during both the migration and breeding seasons (Robertson et al., 2013). Given the potential for habitat generalist species to exploit distributed cropland systems (Stanton, 2018), we predicted that habitat generalists would be more dominant in croplands. We also predicted that an increased proportion of grassland habitat in the surrounding landscape would positively influence all avian communities (i.e. grassland obligates, habitat generalists). Based on findings from Blank et al., 2014, we hypothesized that perennial grasslands would more effectively support species of conservation concern than croplands. Additionally, we hypothesized that PAM would offer a more comprehensive understanding of how potential bioenergy grasslands benefit declining avian populations in agricultural systems compared to traditional methods such as point count surveys (LaGory et al., 2024).

2 | MATERIALS AND METHODS

2.1 | Study site

Acoustic monitors were deployed across six pairs of neighbouring row-crop and grassland fields in Hayes and Hitchcock County, located in southwestern Nebraska (Figure 1). Paired grassland-cropland sites were located >8 km from each other. All of the selected grasslands were enrolled in CRP, a federal initiative managed by the US Department of Agriculture (USDA) Natural

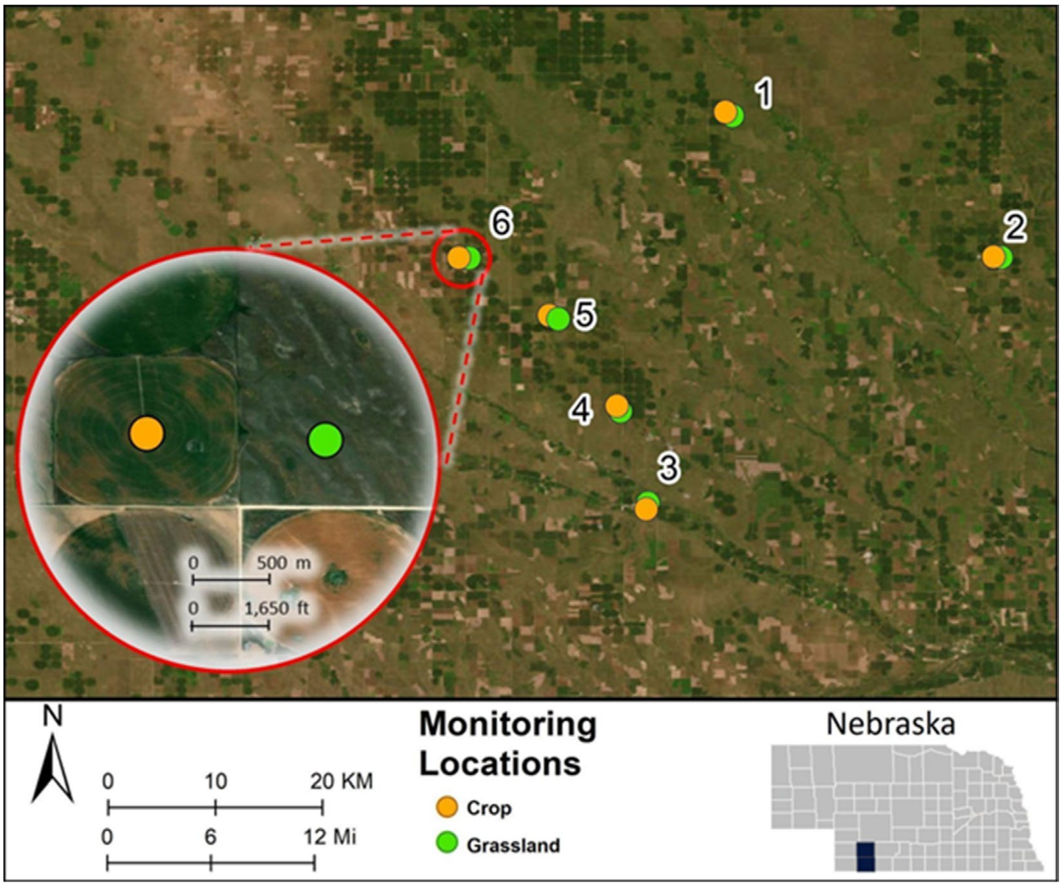

FIGURE 1 The locations of the six paired ARU monitoring sites in southwestern Nebraska from 2022 to 2023.

Resources Conservation Service (Stubbs, 2014). Small amounts of switchgrass were present at the study sites; however, it was not the dominant vegetation type (Table S1), except at one site. Currently, there are few monoculture grassland fields privately grown for bioenergy in Nebraska and most are small agronomic research plots not suited for field-scale research on bird communities (see Mitchell et al., 2008). As a result, we used low-diversity grassland fields as a proxy for monoculture bioenergy grasslands. The sampled row-crop sites included corn (*Zea mays*) and soybean (*Glycine max*) fields with center-pivot irrigation, while one field had a half-pivot irrigation system.

2.2 | Acoustic monitoring

Between March and September of 2022 and 2023, a total of 12 ARUs (Wildlife Acoustics Song Meter Mini, Maynard, MA, USA) were installed, with one ARU deployed at each grassland and cropland field. The ARUs at each paired grassland and cropland field were positioned with a spacing range of 600–755 m between units. The effective ARU detection distance varies by species (Van Wilgenburg et al., 2017), but >100 m is a reasonable threshold for sampling entire bird communities (Darras et al., 2018; Hingston et al., 2018). The ARUs were programmed to capture avian calls from 1 h before sunrise to 1 h after sunrise and from 1 h before sunset to 1 h after sunset. These periods were chosen as they coincide with the times of day when avian vocal activity is most frequent. Within the grassland study field, one ARU was installed at a randomly selected location and in the cropland field, the ARUs were deployed at the pivot center. For a more detailed explanation of the acoustic monitoring methodology, please review Schuster et al. (2024).

2.3 | Landscape analysis

We superimposed the ARU locations onto the 30 × 30 m 2021 National Land Cover Database (NLCD; Dewitz, 2023) layer in ArcGIS Pro v3.3. We only used a single year of the NLCD data layer because it was the most current land cover data available and changes that may have occurred in the 2-year study period were minimal. Land-cover classes were reclassified as cropland, grassland, forest, open water, development and wetlands (Table 1). Hay/pasture and herbaceous grasslands were combined into one class called grassland (as in Blank et al., 2014; Wright & Wimberly, 2013). We used the 'landscapemetrics' package (Hesselbarth et al., 2019) in R to calculate grassland and cropland composition at two spatial scales: 500 m and 1 km (Cunningham & Johnson, 2006; Blank et al., 2014).

2.4 | Recording analyses

We used BirdNET-Analyzer v2.4 to automatically identify bird species from the recordings. We set the system to classify vocalizations from only species detected on eBird (Wood et al., 2011) checklists near the center of all paired sites (40.51° N, −101.02° W). The BirdNET minimum confidence threshold was set to 0.25, and we kept all remaining settings at the default values (sensitivity = 1; overlap = 0). All BirdNET results were saved as tab-delimited data tables for later analysis.

TABLE 1 Reclassified national land cover database (NLCD) land-cover classes.

Reclassified layer	NLCD data type
Cropland	Cultivated crop
Grasslands	Hay/pasture
	Herbaceous grasslands
Forest	Deciduous forest
	Evergreen forest
	Mixed forest
	Shrub/scrub
Open water	Open water
Development	Developed, open space
	Developed, low intensity
	Developed, medium intensity
	Developed, high intensity
Wetlands	Woody wetlands
	Emergent herbaceous wetland
NODATA	Barren land
	Perennial snow/ice

2.5 | Focal species selection

We chose 20 focal species previously selected by Schuster et al. (2024) and filtered BirdNET detections based on the recommended species-specific confidence (SSC) threshold. Although several focal species in this recent study had SSCs below 0.25, we believe that raising the minimum confidence threshold would improve the overall precision of BirdNET and enable us to draw more reliable conclusions. We also aimed to include new focal species in the analysis due to high detection density at the confidence interval of 0.25. To summarize precision for the additional focal species, we randomly selected and confirmed 100 5 s audio clips to calculate BirdNET performance at different confidence intervals. An observer listened to each 5 s audio clip, which included 1 s before and after the 3 s BirdNET spectrogram, to verify the detection of the focal species. Precision was then calculated with the following equation:

$$\frac{\text{true positives}}{\text{true positives} + \text{false positives}}$$

We categorized true-positives and false-positives based on the criteria from Cole et al. (2022). Once we calculated precision, we selected an SSC interval based on if the calculated precision at a given confidence level was ≥0.9 (i.e. we chose the lowest

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confidence interval that gave us a precision of ≥0.9). We used the 'dplyr' and 'av' packages in R to organize, extract and review BirdNET acoustic detections.

2.6 | Calculating species richness

We encountered technological difficulties, leading to several days of missing audio data throughout the sampling period and across sites due to strong winds. Therefore, we filtered recordings to dates in which ARUs in paired sites (grassland and cropland field) collected a full day of recordings ($n = 8$ h). After filtering, we ended up with 838 complete days of recordings in 2022 and 2023 across the six pairs of ARUs. The distribution of complete days of recordings across pairs and weeks is shown in Figure S1. We used these complete recordings to compare richness estimates of focal species, grassland obligates, habitat generalists, and species of conservation need between the two land covers. Most focal species included in the study have been previously documented in low-diversity CRP fields (Roth et al., 2005), switchgrass fields (Robertson et al., 2011), intercropped switchgrass in pine plantations (Loman et al., 2014), and during migration seasons in switchgrass fields (Robertson et al., 2013). Some species were included based on Uden et al. (2015), which identified species of interest for evaluation in bioenergy grass production. After filtering the BirdNET output to the SSC thresholds, we calculated weekly focal species richness and classified species based on their assigned breeding biome from Rosenberg et al. (2019; Table 2) so that we could compare species richness based on breeding habitat.

We also compared the richness of species of conservation need (SCN) that breed in grassland habitats, based on Bomberger-Brown et al. (2012), and total species richness from the 2022 BirdNET output. Verification procedures demonstrated in Schuster et al. (2024) were applied as follows. To confirm the presence of each avian species at each individual field, we manually reviewed the 5-s audio clip for the 10 detections with the highest confidence scores for each species detected. Only species confirmed at least once among the 10 recordings at each grassland and cropland field were included in the species richness calculation, while those not confirmed at least once were excluded from the analysis.

2.7 | Statistical analysis

We fit generalized additive mixed models (GAMM) using the 'gam' function in the 'mgcv' package (Wood, 2011, 2017) to analyse temporal trends and the impact of grassland habitat in the surrounding landscape on focal species richness in both cropland and grassland study fields. Given the complexity of most ecosystems, we anticipated nonlinear relationships between variables. GAMMs are well suited for capturing these complex, nonlinear interactions by incorporating multiple regressions with varying coefficients (Wood, 2017). We developed three hypothesis-driven nonlinear models, informed by previous research (Blank et al., 2014; Herse et al., 2020; Torrenta & Villard, 2017) and field experience, along with a global model and a null model (see Table S2). Our GAMM models had a Poisson error structure and log link function, including the interaction between land cover (grassland or cropland) and week of recording to assess temporal trends. Three response variables were tested: average weekly focal species richness, average weekly grassland obligate species richness and average weekly habitat generalist species richness. To limit multicollinearity in the models, we identified landscape variables with a correlation coefficient >0.7 using a correlation matrix (Brennan et al., 1986). We did not include cropland composition in any of the models because it was negatively correlated with grassland composition at the 1-km scale ($r = -0.96$) and 500 m scale ($r = -0.71$). Given our interest in evaluating the relationship between grassland composition and avian richness, we included two landscape-scale variables in the tested models: grassland composition within 500 m and 1 km buffers. To minimize spatial autocorrelation, we included pair, field (unique field), and year as random effects. In total, our model set included one interaction term, three random effects and variations of two landscape variables, with each variable modeled as a smooth term. As the number of available recordings varied throughout the weeks, we included a weight variable, calculated as the proportion of days within each week that had complete recordings for each pair.

The second-order Akaike's information criteria (AICc) was used to compare the weight of evidence in support of each model for average weekly focal species richness, average weekly grassland obligates species richness and average weekly habitat generalist species richness (Anderson & Burnham, 2002). Models with an $\Delta AICc < 2.0$ units away from the top model were selected and adjusted Akaike weight (w_i) was calculated for each of the top models. Using the 'MuMIn' package (Bartoń, 2024) we model-averaged the top-performing models for each response variable to calculate parameter estimates and variable weights. We then produced predictive models based on model averages.

Due to the interaction between the week of recording and land cover, we also compared response variables across land covers by calculating the difference in weekly richness between the two land covers. This was done using an analysis of variance model (ANOVA) followed by a post-hoc Tukey honestly significant difference (HSD) test. To compare SCN species richness across all monitoring years and the total species richness from the 2022 acoustic data between cropland and grasslands at each pair, we performed two paired Student's t-tests using the 't.test' function in base R. This approach was chosen due to the infrequent or low detection rates of species of conservation need. To understand the arrival and departure times of migrant birds using our study sites, we visualized their phenology using timeline graphs created with the package 'vistime' (Raabe, 2023). All analyses were done in R studio v4.4.1 (R Core Team, 2024).

TABLE 2 The 27 selected focal species, along with their species-specific confidence thresholds and corresponding breeding biomes.

Scientific name	Common name	Species-specific confidence (SSC) threshold	Breeding biome	Previous research
Spinus tristis	American Goldfinch	0.250	Forest generalist	Roth et al. (2005) and Robertson et al. (2011)
Turdus migratorius	American Robin	0.250	Forest generalist	Robertson et al. (2011)
Hirundo rustica	Barn Swallow	0.250	Habitat generalist	Robertson et al. (2011)
Passerina caerulea	Blue Grosbeak	0.250	Forest generalist	Loman et al. (2014)
Cyanocitta cristata	Blue Jay	0.250	Forest generalist	Loman et al. (2014)
Quiscalus quiscula	Common Grackle	0.250	Habitat generalist	Robertson et al. (2013)
Chordeiles minor	Common Nighthawk	0.250	Habitat generalist	—
Spiza americana	Dickcissel	0.250	Grassland obligate	Blank et al. (2014) and Uden et al. (2015)
Tyrannus tyrannus	Eastern Kingbird	0.250	Grassland obligate	Robertson et al. (2013) and Uden et al. (2015)
Ammodramus savannarum	Grasshopper Sparrow	0.448	Grassland obligate	Roth et al. (2005) and Robertson et al. (2011)
Eremophila alpestris	Horned Lark	0.250	Grassland obligate	Robertson et al. (2013)
Zenaida macroura	Mourning Dove	0.250	Habitat generalist	Robertson et al. (2013)
Colinus virginianus	Northern Bobwhite	0.250	Forest generalist	Uden et al. (2015)
Agelaius phoeniceus	Red-winged Blackbird	0.250	Habitat generalist	Roth et al. (2005) and Blank et al. (2014)
Phasianus colchicus	Ring-necked Pheasant	0.250	Introduced	Roth et al. (2005), Robertson et al. (2011) and Uden et al. (2015)
Passerculus sandwichensis	Savannah Sparrow	0.250	Grassland obligate	Roth et al. (2005) and Robertson et al. (2011)
Tachycineta bicolor	Tree Swallow	0.505	Habitat generalist	Robertson et al. (2011)
Tyrannus verticalis	Western Kingbird	0.250	Grassland obligate	—
Sturnella neglecta	Western Meadowlark	0.250	Grassland obligate	Roth et al. (2005) and Uden et al. (2015)
Meleagris gallopavo	Wild Turkey	0.250	Forest generalist	Roth et al. (2005)
Vireo bellii	Bell's Vireo	0.250	Arid lands	—
Molothrus ater	Brown-headed Cowbird	0.250	Habitat generalist	Robertson et al. (2013) and Uden et al. (2015)
Athene cunicularia	Burrowing Owl	0.250	Grassland obligate	—
Spizella pallida	Clay-coloured Sparrow	0.250	Grassland obligate	Robertson et al. (2011) and Robertson et al. (2012)
Charadrius vociferus	Killdeer	0.250	Habitat generalist	Robertson et al. (2013)
Bartramia longicauda	Upland Sandpiper	0.250	Grassland obligate	Roth et al. (2005) and Uden et al. (2015)
Pooecetes gramineus	Vesper Sparrow	0.800	Grassland obligate	Robertson et al. (2011)

Note: This table also includes previous studies that have assessed or referenced the responses of focal species to potential bioenergy grasslands and croplands.

3 | RESULTS

In addition to the species list and performance metrics from Schuster et al. (2024), we manually verified and calculated precision estimates for seven additional species, bringing the total to 27 focal species (Table 2). This group was further divided into grassland obligates ($n=11$) and habitat generalists ($n=8$) based on their breeding biomes. At the 500 m scale, the landscape around the ARUs consisted mostly of croplands (mean = 51.12%, range = 11.64%–86.61%; Figure S2A) and grasslands (mean = 42.90%, range = 9.04%–82.65%; Figure S2A). The 1 km radius around each of the ARUs was primarily composed of grasslands (mean = 50.59%, range = 34.40%–75.87%; Figure S2B) and croplands (mean = 42.84%, range = 21.52%–62.45%; Figure S2B). We collected a total of 13,779 h of acoustic recordings at all monitoring locations (2022: 6144 h, 2023: 7635 h). BirdNET made a total of 3,399,887 species detections from these recordings at a confidence threshold of 0.25. Of these detections, 3,241,157 (95%) were the 27 focal species (Table 2). The five most frequently detected species were Grasshopper Sparrow (*Ammodramus savannarum*), Western Meadowlark (*Sturnella neglecta*), Dickcissel (*Spiza americana*), Horned Lark (*Eremophila alpestris*) and American Robin (*Turdus migratorius*). Collectively, these five species accounted for over 81% of all BirdNET detections.

A total of 94 avian species, including seven grassland-breeding SCN, were detected and confirmed from the audio data. Three focal species were classified as SCN and were therefore included in the SCN richness calculation. We found that grasslands supported a significantly higher number of grassland-breeding SCN compared to croplands ($\Delta = 2.33$, $p < 0.01$, $t = 4.72$, 95% confidence interval: 1.06–3.60; Figure S3). When we compared the total avian species' richness, our results showed that an average of 17 more species were detected in grasslands compared to croplands in 2022 ($p < 0.01$, $t = -6.82$, 95% confidence interval: 11.57–22.59; Figure S3).

3.1 | Focal species

The top-performing model for average weekly focal species richness was *week × cover + grassland_500 + random effects* (*Pair*, *Field*, *Year*; Table 3), followed by the global model (Table S3). In the grassland and cropland study fields, average weekly focal species richness peaked during week 19 and 20 (mid-May), then gradually declined thereafter, with grassland cover at the 500 m scale having a significant impact on richness ($p = 0.04$). Predicted average weekly focal species richness followed a concave distribution, with richness peaking at 35%–45% grassland cover within a 500-m radius in both field types but decreasing as grassland cover approached 100% (Figure 2a). In contrast, grassland cover at the 1-km scale had no significant impact on average weekly focal species richness in grasslands or croplands (Figure 2b). The global model showed a significant relationship between the week of recording and both land covers when predicting focal species richness ($p < 0.01$). For the full model output for all tested models (see Table S3); smooth terms and diagnostic plots are provided in Figures S4–S9.

3.2 | Grassland obligate species

The global model was the most parsimonious model for grassland breeding birds (Table 3) and the second-best model was *week × cover + grassland_500 + random effects* (Table S3). Similar to the focal species richness model, the top-performing model for weekly average grassland obligates showed peak richness during Weeks 19 and 20 in grassland fields, while in croplands, richness peaked between Weeks 18 and 24. Grassland composition at the 500 m scale ($p < 0.01$) and 1 km scale ($p = 0.01$) had a significant impact on average weekly grassland breeding bird richness (Figure 2a,b). At the 500 m scale, average weekly grassland obligate richness peaked at around 50% grassland cover and decreased in both field types, although this relationship was more pronounced in grassland study fields. Whereas, at the 1 km scale, average weekly richness increased consistently with grassland cover, showing a clear positive relationship that was again stronger in grassland study fields.

3.3 | Habitat generalist species

For average weekly habitat generalist species richness, the top-performing model was *week × cover + grassland_1 + random effects* (Table 3), which showed a significant relationship between richness and grassland composition at the 1 km scale ($p < 0.01$). The next best model was the *week × cover + grassland_500 + random effects* (Table S3), which also showed a significant relationship between grassland composition at the 500 m scale ($p < 0.01$). Predicted average weekly habitat generalist's species richness declined at approximately 40% grassland cover at the 500 m scale (Figure 2a) with a similar negative relationship observed at the 1 km scale (Figure 2b).

Except for the null model, all the best-performing models for average weekly focal species richness, average weekly grassland obligate species richness and average weekly habitat generalist species richness exhibited high R^2 values (mean = 0.61, 0.60 and 0.56, respectively; Table S3). Based on model-averaged predictions, the week of recording, in combination with land cover and grassland composition at both the 500 m and 1 km scales, was an important predictor of focal species richness, grassland obligates and habitat generalists.

TABLE 3 Top-performing models associated with the average weekly focal species richness, grassland breeding bird species richness and habitat generalist species richness in southwestern Nebraska, 2022–2023.

Avian response variable	Model	AICc	Adjusted w_i	R^2
Focal species richness	*s(week × cover)*** + s(grassland_500)* + s(pair("re")) + s(field("re"))*** + s(year("re"))*	5419.38	0.27	0.70
Grassland obligate species richness	*s(week × cover)*** + s(grassland_500)*** + s(grassland_1)* + s(pair("re")) + s(field("re"))** + s(year("re"))*	4122.25	0.42	0.69
Habitat generalist species richness	*s(week × cover) *** + s(grassland_1)** + s(pair("re"))*** + s(field("re")) + s(year("re"))*	3603.15	0.27	0.61

Note: Asterisks denote significance of variables in a model (* ≤ 0.05, ** ≤ 0.01, *** ≤ 0.001).

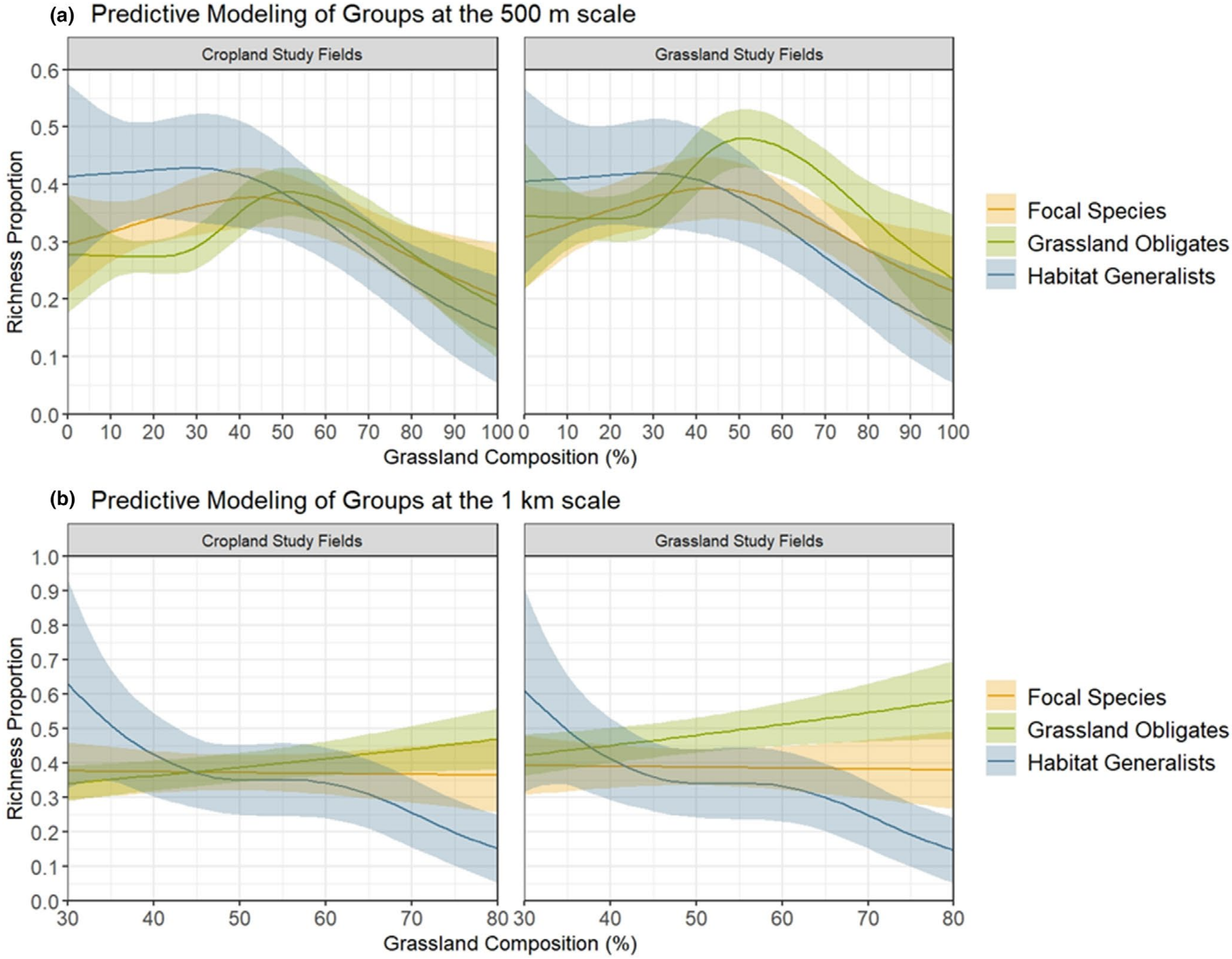

FIGURE 2 Relative proportion (predicted richness/total species) in species richness for focal species ($n = 27$), grassland obligates ($n = 11$) and habitat generalists ($n = 8$) at both scales, with data separated by whether the study field was in grassland or croplands in southwestern Nebraska, 2022–2023. Panel (a) represents species richness for all groups at the 500 m scale and panel (b) represents species richness for all groups at the 1 km scale.

The interaction between land cover and week of recording was significant in all top-performing models for each of the three avian response variables. Our post-hoc Tukey HSD test revealed temporal variations in average weekly focal species richness, with some weeks showing significantly higher richness in grasslands, while other weeks exhibited greater richness in croplands (Figure 3a). Overall, average weekly grassland obligate species richness was significantly higher in grasslands throughout most of the sampling period, except during mid-March through early April (Figure 3b). Average weekly habitat generalist richness was higher in croplands for the bulk of the season (Figure 3c). Both grassland obligate and habitat generalist average weekly species richness shifted between grasslands and croplands during Week 16 (mid-April). To explain this variability in the difference in richness, we analysed the timeframe each species was detected on the study sites across complete days. The timeline for grassland obligations shows that the two species that were present during the early weeks were Horned Lark and Western Meadowlark (Figure S10). Arrival and departure dates for habitat generalists were highly variable across the sampling years (Figure S11).

4 | DISCUSSION

Rising human populations, growing energy demands and volatile petroleum markets, coupled with risks associated with climate change, have sparked increasing interest in alternatives to fossil fuels. Currently, corn is the predominant feedstock for biofuels; however, perennial grasses, such as switchgrass, have been identified as a promising alternative due to their capacity to maintain soil structure, their high yield and nutrient efficiency, and their low requirements for chemical, energy and water inputs (Fletcher Jr et al., 2011). Perennial energy crops have the capacity to increase biodiversity at multiple levels, including positively impacting the diversity of breeding bird populations (Werling et al., 2014). The suitability of potential bioenergy grasslands to provide habitat for declining grassland

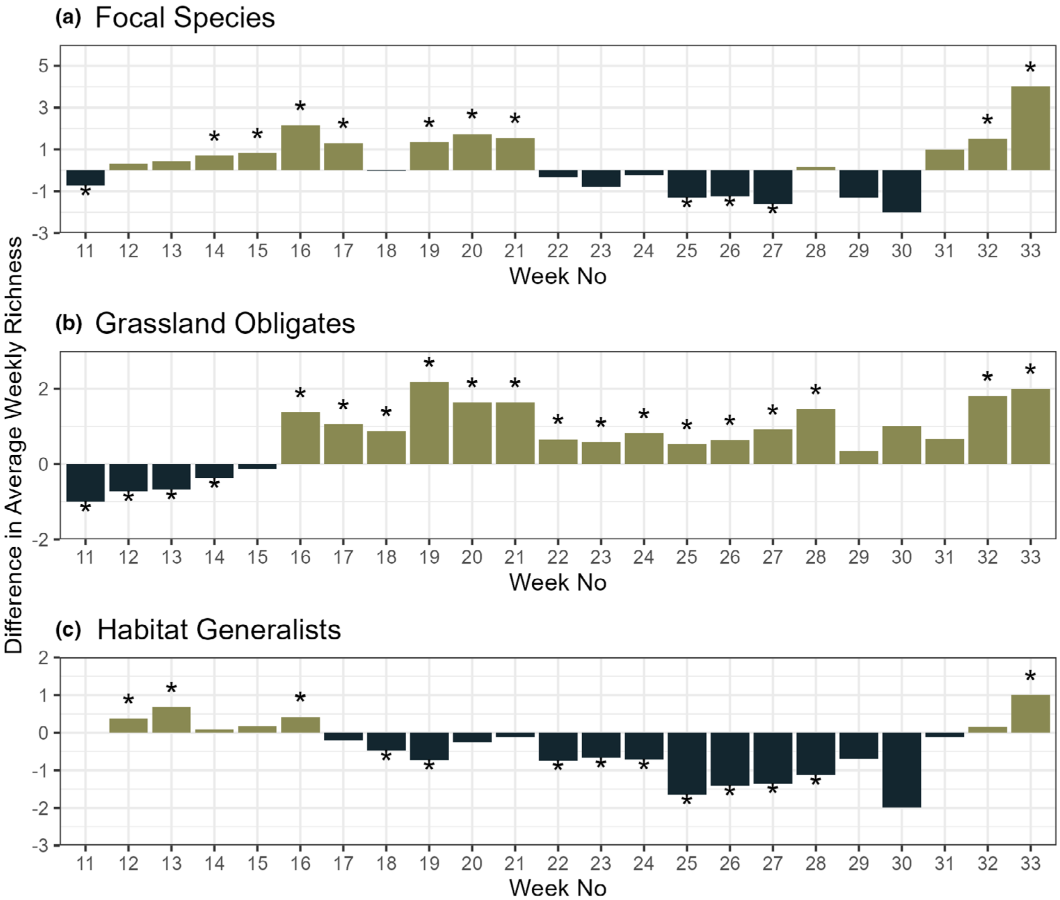

FIGURE 3 Difference in average weekly richness between each land cover type for focal species richness, grassland obligates and habitat generalists. Yellow bars represent higher richness in perennial grasslands and black bars represent higher richness in croplands. Asterisk denotes a significant difference ($p \leq 0.05$) between the two land types based on the post-hoc Tukey HSD test. Week 11 corresponds to mid-March. Panel (a) represents focal species, panel (b) represents grassland obligates speciess, and panel (c) represents habitat generalist species richness.

bird species has been studied using traditional methods (Blank et al., 2014; Robertson et al., 2011; Roth et al., 2005). However, the prolonged impact of these grassland fields compared to monoculture crops throughout both the migration and breeding seasons has been severely underdeveloped. We compared avian population metrics between row-crop and low-diversity CRP fields, suitable for conversion to bioenergy grasslands, using PAM.

Compared to row-crop agriculture, perennial grasslands supported greater richness of grassland-breeding SCN and total species richness (Figure S3), which coincides with previous research (Blank et al., 2014). We also assessed the impact that grassland habitat in the surrounding landscape has on average weekly focal species, grassland obligate species and habitat generalist species richness in these fields. Based on model averaging, grassland composition in the surrounding landscape did have significant impacts on each of these avian groups. Moderate amounts (20–50%) of grassland habitat in the surrounding landscape at the 500 m scale positively affected focal species and grassland obligates in both grassland and cropland study fields, with the highest richness of grassland obligates observed in grassland fields that had approximately 50% grassland cover within this 500 m area. Further, average weekly grassland obligate species richness had a clear positive relationship with grassland composition at the 1 km scale. Whereas, increasing grassland habitat within 500 m and 1 km of the study sites had a clear negative impact on habitat generalists. Given the negative correlation between cropland and grassland composition at both scales ($r > 0.7$), habitat generalist species may be less impacted by the expansion of row-crop agriculture relative to grassland obligates and SCN. Our analysis indicated that grassland composition at smaller spatial scales positively impacts average weekly focal species and grassland obligate species richness up to a certain threshold. In contrast, at larger spatial scales, more grassland habitat is consistently better for grassland specialist species. Wildlife responds differently to habitat composition depending on spatial scales. Specifically, local habitat heterogeneity may support a broader array of avian species, while greater grassland availability at larger scales benefits grassland specialists. Therefore, integrating perennial bioenergy grasslands on marginal lands adjacent to row-crops would enhance ecological function in agricultural landscapes (Werling et al., 2014) by expanding total grassland cover at broader scales while maintaining landscape diversity. Intertwining grassland habitat into agricultural landscapes to create connections between existing grassland areas not only expands the overall grassland habitat but also provides significant benefits to area-sensitive avian species (Blank et al., 2014, 2016), which includes many grassland birds.

One possible explanation for the concave relationship between grassland composition and focal species richness, as well as grassland obligates at the 500-m scale, could be the ambiguous ecological advantage of irrigation ponding and the availability of water in croplands. This could benefit grassland birds in a historically arid region, particularly considering that Hayes County had 42,738 acres of farmland irrigated in 2022 (National Agricultural Statistics Service, 2022). Research related to birds' responses to agricultural irrigation is scarce (Cabodevilla et al., 2022), but it has been suggested that while irrigation can positively impact species richness on a small scale, it may also negatively affect bird communities by replacing specialist species with generalists (Giralt et al., 2021). At the 500 m scale, focal species and grassland specialists may be taking advantage of water availability at these sites. However, an increase in irrigated cropland area in this region would likely boost the presence of habitat generalist species due to the negative correlation between grassland and cropland composition. Our findings align with previous research, suggesting that water availability from irrigation can offer localized benefits to avian communities. The expansion of irrigated cropland at the landscape scale would be detrimental to grassland obligate communities, as it replaces the grasslands with habitat that would support habitat generalist species. Non-irrigated perennial grasslands near irrigated cropland, on the other hand, could support a wider diversity of avian species within agroecosystems.

Our PAM framework allowed us to explore temporal patterns in average weekly avian species richness between two distinct agricultural land uses. Overall, average weekly focal species richness did not temporally differ between the two land uses, with focal species richness being significantly higher in grasslands during some weeks and greater in croplands during others (Figure 3a). Conversely, grassland obligates had higher richness in perennial grasslands for most of the sampling season (Figure 3b). This aligns with previous studies, which also found that grassland obligate species may benefit most from the inclusion of perennial grasslands, such as switchgrass, as opposed to more generalist species (LaGory et al., 2024; Robertson et al., 2011). Habitat generalists exhibited higher species richness throughout most of the sampled season in croplands, solidifying their ability to exploit non-native habitat (Stanton et al., 2018). The temporal analysis revealed seasonal habitat shifts in both habitat generalist and grassland obligate species in early to mid-April, which may be linked to migration timing, breeding, or habitat availability. Notably, candidate bioenergy feedstocks have been shown to support avian populations during breeding (Blank et al., 2014) and migratory seasons (Robertson et al., 2012). Further research is needed to understand how the timing of management strategies, such as harvesting and chemical applications, in both traditional row-crops and bioenergy grasslands may influence the value of these systems to bird communities across seasons.

Our inclusion of non-monoculture grassland fields, rather than switchgrass or other bioenergy grassland plantings, may have influenced the applicability of our results. Birds are attracted to bioenergy grasslands that feature higher plant species richness and greater abundance of forbs compared to monoculture grass fields (Blank et al., 2014). We used low-diversity CRP grasslands as proxies for grasslands dedicated to bioenergy production due to the limited availability of larger, dedicated bioenergy plots, which are typically confined to small agronomic research areas in Nebraska (see Mitchell et al., 2008). As such, our results are more applicable for bioenergy grassland designs that incorporate small amounts of plant species diversity rather than monoculture grasslands. Feedstocks with higher plant diversity may have lower conversion potential and profitability than monoculture feedstocks (Griffith et al., 2011). This leads to management practices that prioritize increased grass cover, structural uniformity, and reduced plant diversity, which could potentially impact avian use of these grasslands. Incorporating plant diversity into bioenergy grasslands could facilitate the coexistence of avian populations and bioenergy production, but the threshold at which plant species diversity could significantly reduce conversion potential must be carefully considered.

Our analysis included several species that have not been previously examined in studies assessing the habitat value of bioenergy crops. We included two species that are Tier 1 at-risk species in southwestern Nebraska (i.e. Bell's Vireo and Burrowing Owl; Bomberger-Brown et al., 2012) and Common Nighthawk. We also included and classified Western Kingbird (*Tyrannus verticalis*) as a grassland obligate species of interest, which may not be applicable to other environments. In Nebraska, this species migrates to breed and selects habitats differently across spatial scales, often favouring areas with widely spaced trees and substantial grass cover (Bergin, 1992). As an insectivore, the Western Kingbird may benefit from increased prey availability in switchgrass or other perennial grasslands (Werling et al., 2014), which is another reason we classified this species as a grassland obligate in the region. The biome classification of our focal species could have influenced our results, as these species may respond differently to bioenergy production depending on the landscape.

PAM offered a more comprehensive evaluation of avian occupancy of perennial grasslands, enabling a deeper comparison of this land use with croplands over an extended period. LaGory et al. (2024) also highlighted the benefits of using PAM over point counts, as it enabled researchers to assess year-to-year variation in bird detection, offering valuable insight into how switchgrass maturity may influence avian use. The data collection standardization and data capacity available with PAM, similarly, allowed for the documentation of weekly variations in focal species populations in grassland and croplands. The ability to sample SCN, often overlooked during point count surveys, provided the opportunity to better assess habitat use by these threatened species throughout their annual cycle. Broader temporal and geographical sampling, along with reduced observer bias and cost-effectiveness, are key advantages of PAM, making it a valuable method for inclusion in ecological research (Sugai et al., 2019). One overlooked benefit of PAM is that it enables enhanced sampling in rural areas that are regularly under-represented in traditional monitoring efforts, due to their low population density (similar to McGovern et al., 2024). Sampling in rural areas with low population density presents logistical and safety challenges, such as difficulty finding trained personnel and increased risk to technicians working alone in remote locations without immediate support in case of an emergency. The application of PAM in rural agricultural landscapes could enhance our understanding of how migratory avian species utilize various bioenergy crops and other habitats, while also offering insights into how these patterns may shift under future bioeconomic scenarios.

There are some limitations to this technology that should be considered, such as technical malfunctions in the ARU technology resulting in the loss of acoustic data. Several other researchers have come across other technological malfunctions or storage-related failures that have impacted data availability (Dixon et al., 2023; Ware et al., 2023; Wightman et al., 2022). Anticipating potential data loss at various stages of PAM is essential for the success of research applications. Another limitation is the lack of analysis procedures to estimate avian density or population metrics from sound recordings without additional sampling (i.e. point count surveys; Pérez-Granados & Traba, 2021). While our results revealed differences in species richness, it is possible that abundance estimates might have yielded different outcomes, potentially offering a more nuanced understanding of avian populations in grasslands and croplands. Future research should focus on testing various approaches that can reduce bias and resource use, with the aim of improving bird density estimates from acoustic recordings.

The conversion of monoculture row-crops to switchgrass has demonstrated positive impacts on avian populations through scenario planning. However, these studies lacked field evaluations of grassland bird communities (Uden et al., 2015). Our findings provide support for the inclusion of perennial grasslands, potentially used for bioenergy production in intensified cultivated landscapes, with the goal of benefiting avian populations. Most notably, including perennial grasslands on marginal acres of cropland could benefit SCN that breed in grasslands (Robertson et al., 2012). However, grasslands dedicated to bioenergy production may lack the vegetative diversity necessary to support avian populations. As a result, replacing highly diverse CRP fields with monoculture bioenergy grasslands, without additions of other grassland habitat in the landscape, could have detrimental consequences for bird populations (Uden et al., 2015). By comparing avian communities in grasslands and adjacent croplands, our results demonstrate the season-long benefits of integrating these bioenergy grasslands into agricultural systems. Developing and utilizing a diverse range of feedstocks is important to sustainably meet biorefinery supply demands, but this can only be achieved through policies and strategies that prioritize environmental sustainability and benefits (Long et al., 2015). Incorporating switchgrass and other perennial energy crops as novel feedstocks, alongside traditional crops like corn, will enable the comprehensive advancement of a viable bioeconomy without further degrading avian populations.

5 | CONCLUSION

Incorporating bioenergy grasslands into agricultural landscapes could benefit avian populations, especially if these grasslands strategically replace intensively cultivated annual row crops such as corn. This bioenergy conversion could be particularly beneficial to SCN and other grassland-breeding avian species. PAM allowed us to uncover important temporal relationships in avian community responses to this land use conversion scenario. As the bioeconomy continues to evolve and reshape agricultural landscapes, it is essential to consider the environmental benefits of these changes to ensure long-term sustainability.

AUTHOR CONTRIBUTIONS

Leroy J. Walston conceived the ideas and, in collaboration with Andrew R. Little, designed the methodology. Grace E. Schuster was responsible for data collection, while she and Leroy J. Walston analysed the data. Both Grace E. Schuster and Leroy J. Walston led the writing of the manuscript. Andrew R. Little provided edits through the writing process. All authors made critical contributions to the drafts and provided final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare that no competing interests exist.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

The data are publicly available and can be accessed and downloaded from Zenodo at https://doi.org/10.5281/zenodo.17136519 (Schuster, 2025).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Table S1. Program type and description of Conservation Reserve Program (CRP) enrollment for each grassland study site as well as dominant vegetation at each site.

Table S2. The three-hypothesis driven models.

Table S3. Full model output for average weekly focal species, grassland obligate species and habitat generalist species richness.

Figure S1. Distribution of complete days of recordings each week by pair which include both a grassland and cropland site with full (8 h) of recordings.

Figure S2. Bar graph depicting composition of grasslands and croplands in the surrounding landscape around acoustic monitoring locations, measured at two spatial scales: 500 and 1 km.

Figure S3. Boxplot results from two-paired Student's *t*-tests comparing total species richness and species of conservation need (SCN) richness between croplands and grasslands.

Figure S4. Smooth term plots for top-performing model for predicting average weekly focal species richness in southwestern Nebraska, 2022–2023.

Figure S5. Diagnostic plots for top-performing model for average weekly focal species richness.

Figure S6. Smooth term plots for top-performing model for predicting average weekly grassland obligate species richness in southwestern Nebraska, 2022–2023.

Figure S7. Diagnostic plots for top-performing model for average weekly grassland obligate species richness.

Figure S8. Smooth term plots for top-performing model for predicting average weekly habitat generalist species richness in southwestern Nebraska, 2022–2023.

Figure S9. Diagnostic plots for top-performing model for average weekly grassland obligate species richness.

Figure S10. Timeline of the first and last detections of grassland obligate focal species in 2022–2023 across both grassland and cropland habitats. Green horizontal line represents ARU deployment and the red horizontal line represents ARU removal during both years.

Figure S11. Timeline of the first and last detections of habitat generalists focal species in 2022–2023 across both grassland and cropland habitats. Green horizontal line represents ARU deployment and the red horizontal line represents ARU removal during both years.

Figure S12. Acoustic monitor installed in a grassland field.

Figure S13. Acoustic monitor installed in a cropland field.

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