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Passive monitoring of avian habitat on working lands

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Abstract

Intensive agricultural landscapes pose a challenge to wildlife managers, policymakers, and landowners hoping to increase the diversity of desired wildlife species, such as grassland birds, which require urgent conservation action. In intensive agricultural landscapes, like those of the Midwestern United States, most land area is privately owned and operated and managed primarily for production. Thus, conducting ecological research in intensive agricultural landscapes requires collaborative approaches aimed at farm owners and operators. Recent advances in acoustic data collection and high-resolution habitat mapping, including low-cost acoustic recorders and satellite remote sensing, may be well positioned to address this challenge by enabling expanded assessments and monitoring of wildlife populations and habitats across regions. This study examined fine-grained habitat characteristics and their relationship with avian biodiversity in intensive agricultural landscapes at 44 agricultural sites across the state of Iowa. Passive acoustic monitoring and manual identification of bird species allowed for measurement of vocalizing bird richness. High-resolution mapping of noncrop vegetation provided detailed information on small noncrop vegetation habitat complexes within row-crop agriculture. Measures of image texture provided characterizations of compositional heterogeneity within noncrop vegetation. General linear Poisson modeling demonstrated robust associations between noncrop vegetation and vocalizing bird richness, yet variation in grassland bird richness was not well predicted by noncrop vegetation. Noncrop vegetation texture demonstrated potential as a predictor of vocalizing bird richness, though not better than or when combined with noncrop vegetated area, indicating it may not be an independent measure of habitat quality. Passive acoustic monitoring resulted in useful data at 44 out of 60 originally selected sites, with some lost to failed recorders and/or collaboration issues. Challenges remain in detecting habitat characteristics that promote grassland birds in row crop landscapes. Working toward probabilistic research design across privately owned working landscapes and incorporating more detailed management practice information would improve the transferability of this approach to farmland management and policy.

KEYWORDS
agroecology, biodiversity conservation, citizen science, collaborative, cooperative, multifunctional landscapes, noncrop vegetation, small habitat patches, texture, working landscapes

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INTRODUCTION

Retention and management of noncrop vegetation embedded in agricultural landscapes through set-aside field programs and widened field margins can increase animal biodiversity in working landscapes (Case et al., 2020; Garibaldi et al., 2021; Kremen & Merenlender, 2018; Lee & Goodale, 2018; Schulte et al., 2017). In this study, we investigated methods for mapping noncrop vegetation and monitoring birds in landscapes dominated by row-crop agriculture. We worked with farmers and landowners to install acoustic recorders on their land to determine vocalizing bird species richness and mapped noncrop vegetation at high resolution. We then used the information collected to assess the relationship between acoustically measured avian species richness and patterns of noncrop vegetation.

Monitoring animal biodiversity in small habitats within agricultural landscapes at high spatial and temporal resolution can require extensive fieldwork to map habitats and monitor species, resulting in increased costs and limiting the quantity of observations available to make statistically robust inferences. Advances in high-resolution optical remote sensing to gather habitat vegetation characteristics and passive species detection techniques like acoustic monitoring and camera traps increase the potential to passively generate more observations of relevant ecological data at low cost (Turner, 2014). Moreover, because acoustic monitors and camera traps are typically small and easy to install, they are easy to extend into production-oriented landscapes. Biodiversity monitoring frameworks in agricultural landscapes are especially reliant on high-resolution data because farm management tends to create small and/or narrow noncrop habitat spaces that cannot be observed directly in moderate-resolution 30-m imagery (O'Connell et al., 2015). Fine-scale vegetation mapping has improved with a new generation of microsatellites, reducing historic trade-offs between spatial and temporal resolution (Houborg & McCabe, 2016).

High-spatial-resolution imagery for habitat mapping does not provide all the information necessary to understand habitat quality of a noncropped space. For instance, even if high-spatial-resolution imagery is used, a low thematic resolution of land-cover classes can limit the observation of variations in habitat quality. Hay fields, remnant prairies, pastures, and grassy waterways may qualify as a single land-cover class (e.g., noncrop vegetation) but can have vastly different levels of habitat quality depending upon plant species assemblages and the nutritional value of individual plant species and animal species requirements (Mccracken & Tallowin, 2004; Nocera et al., 2007). Yet, producing land-cover classifications with detailed classes across broad regions remains challenging due to similar spectral reflectance within herbaceous vegetation patterns (Lark et al., 2017; Rashford et al., 2013). One way to address the habitat generalization inherent in discrete land-cover maps is to use image texture analysis, which provides a continuous measure of spectral variation that is thought to be analogous to habitat heterogeneity (Palmer et al., 2002). Texture measures have shown promise as useful predictors of avian species richness over broad extents with moderate-resolution imagery (Duro et al., 2014; Farwell et al., 2020). However, such measures have yet to be assessed with high-resolution imagery in agricultural landscapes, where texture could potentially provide field-level information on the diversity of habitat within noncrop vegetation.

Biodiversity monitoring requires large numbers of local observations in the field to verify wildlife response to remotely sensed habitat characterizations. Passive acoustic monitoring of farmland birds provides a pathway for cost-effective biodiversity monitoring in agricultural landscapes with a large number of observations (Dixon et al., 2020). Passive acoustic monitoring has many advantages over traditional point count methods, including a reduction in altered bird behavior due to human presence, simultaneous observation, long-duration observations, long-term storage of observations, increased sample size with reduced manpower, and the ability to utilize citizen scientists for data collection (Gasc et al., 2017; Sugai et al., 2019). A comparison of point count and acoustic monitoring with active listening providing a count of species during a single observation session found that both methods captured similar species richness (Alquezar & Machado, 2015). Moreover, long-term acoustic monitoring results can outperform point counts that occur over a short set of field visits (Darras et al., 2018; Klingbeil & Willig, 2015).

Small, portable, passive acoustic monitors that do not require excessive configuration in the field offer potential for shared data collection with volunteer collaborators. Collaboration with citizen scientists in making ecological observations is already widely used in avian distribution data sets, such as eBird and UK and US breeding bird surveys (Sullivan et al., 2009). Many new autonomous acoustic sensors offer low-cost, open-source observations that are competitive with commercially available technology (Hill et al., 2018; Sethi et al., 2018). Low-cost sensors lower the barrier to entry for biodiversity monitoring and can be designed specifically as recording devices for monitoring animal biodiversity (Hill et al., 2018) or as repurposed voice recorders or smartphones (Aide et al., 2017; Farina et al., 2014).

In this paper, we expand on prior work relating small habitat patches in row-crop agricultural landscapes to

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vocalizing bird species richness (VBRICH) using passive acoustic monitoring (Dixon et al., 2020). VBRICH is the total number of unique bird species identified from vocalizations in recordings. Our research objective was to examine the habitat value of noncrop vegetation in intensive row-crop landscapes using passive acoustic monitoring and remotely sensed habitat characteristics while navigating the challenges of collaborative ecological research on private lands. Demonstrating progress in the use of acoustic recordings to monitor avian species richness could help land managers assess efforts to improve biodiversity in intensive agricultural landscapes (Fahrig, 2017; Riva & Fahrig, 2022; Tscharntke et al., 2012). Conservation action for grassland birds in the study region is particularly urgent because of ongoing population declines (Stanton et al., 2018).

Here we apply two remotely sensed landscape composition measures to investigate noncrop vegetation management in relation to bird species richness in an intensive agricultural region: total habitat area measured by land-cover classification and habitat heterogeneity using image texture analysis. We assessed four hypotheses that might explain noncrop vegetation habitat value for all birds observed, as well as groups of grassland and nongrassland species. The first hypothesis predicts that VBRICH is best explained by habitat area, the second that VBRICH is best explained by habitat heterogeneity alone, the third that these two variables jointly explain VBRICH, and the fourth that habitat area and habitat heterogeneity are both jointly significant and have an interactive effect.

METHODS

Study area

The US state of Iowa was chosen as the study region because its extensive row-crop agriculture makes it representative of the US Corn Belt (Green et al., 2018) (Figure 1). Intensification of row-crop management over the past 50 years has resulted in 98% of all crops being corn and soybeans (Boryan et al., 2011; Corry, 2016). Cropland interventions such as grassed waterways, contour prairie strips, and set-aside fields are present, although a simplified and homogeneous landscape of rotating corn and soybean fields with minimal noncrop vegetation dominate the region. Moreover, most noncrop vegetation elements of significant size, such as hayfields or grassed waterways, are planted with a monoculture of smooth brome (*Bromus inermis*) or tall fescue (*Festuca arundinacea*) and are commonly hayed at least once per year (Jackson et al., 1996).

Selection of research sites

The objective of the passive acoustic monitoring was to obtain a sample of vocalizing birdlife within intensive row-crop agriculture in Iowa (Figure 2). A sample design of convenience feasible within budgetary and logistical constraints was organized through outreach with farmers and landowners, some of whom operated as collaborators by installing the recorders themselves and others who allowed access to their land. Sixty recorders were available

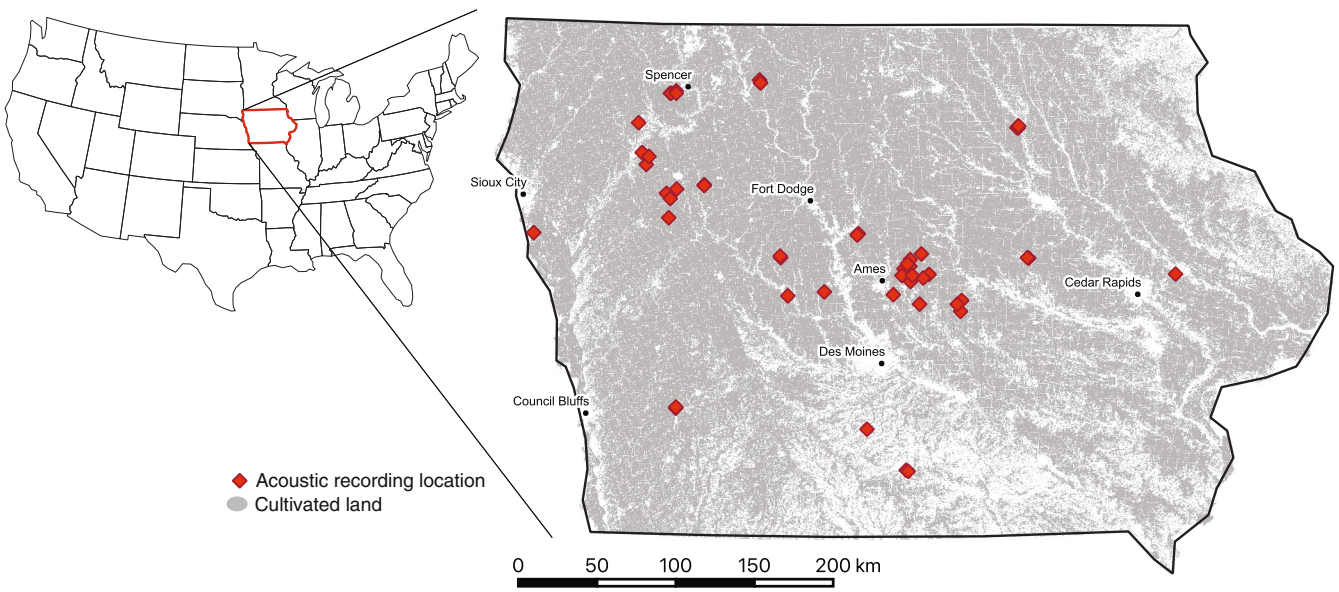

FIGURE 1 Acoustic recording locations on Iowa farmland in June 2019. Cultivated land derived from 2019 USDA Cropland Data Layer (Boryan et al., 2011).

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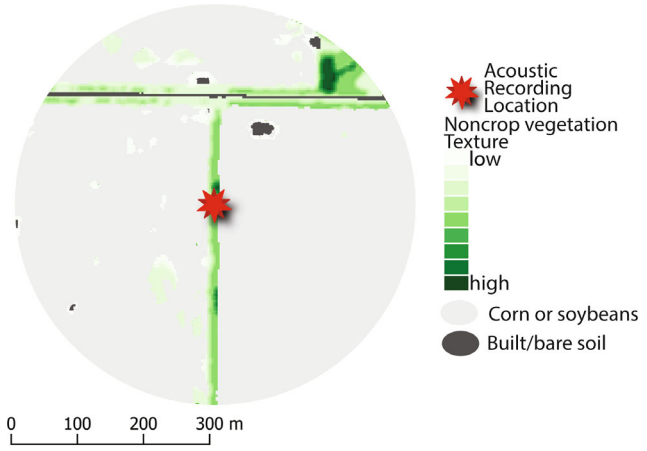

FIGURE 2 Conceptual map illustrating data collection process. Noncrop vegetation area and texture were assessed within 300 m of acoustic recording location. Other landscape components such as crops or built areas were not included in the analysis.

for the study. Landowners were first contacted through a local farming organization (https://practicalfarmers.org) and asked whether they would be willing to receive and install an acoustic recorder, provide a reference to other landowners, or allow Adam Patrick Dixon access to their land to install the recorder (Appendix S1). A total of 15 landowners with land under row-crop agriculture volunteered to host an acoustic recorder. In these cases, recorders were sent directly to the collaborators in the mail with detailed instructions for installation and data collection. In several cases, more than one recorder was sent. This led to a total of 25 recorders sent to collaborators. The remaining 35 recorders were installed and managed by Adam Patrick Dixon on farmland where access permission was granted. This included five Iowa State University Research and Demonstration Farms (ISRFs). Placement of acoustic recorders was determined in dialogue with collaborators and landowners with the intention of imitating as close to a probabilistic sample of row-crop agricultural landscapes in Iowa as possible to maintain statistical assumptions. As a communication aid, potential collaborators were provided a map of the most intensively cultivated places in Iowa. The map communicated the study's focus on intensive row-crop agriculture rather than woodlands or riparian areas at the outset (Appendix S1: Figure S1). Dialogue by voice or electronic communication with potential collaborators reinforced study objectives to avoid bird species associated with wooded or wet ecosystems and to capture bird species associated with cropland systems (Kirk et al., 2020). Recorder locations were required to be near a row-crop field edge and at least 100 m from woodland or wetland. Infrastructure beyond fencing, such as buildings, and paved roadways with potential noise interference with recordings were to be avoided. Recording locations were at least 200 m apart to correspond with traditional avian point count methods and to avoid spatial autocorrelation between sampled landscapes (Hutto et al., 1986). These desired recording location conditions and several visual aids, including the noncrop gradient map, high-resolution satellite imagery on Google maps (maps.google.com), and property boundary maps from a local directory service (farmandhomepublishers.com), were used in consultation with collaborators to determine the approximate recorder installation locations. The resulting sample population represented row-crop agricultural systems from a personal network of Iowa farmers during the month of June.

Acoustic data collection and processing

Passive acoustic monitoring was conducted with AudioMoth recorders. An AudioMoth is a low-cost and lightweight acoustic recording unit (versions 1.0 and 1.1 used), engineered as an open-source engineering and software design (Hill et al., 2018). At each site, an AudioMoth unit was placed within a plastic bag, which was sealed and taped to exclude moisture and secured at a height of approximately 1 m by fastening to a fence post, *t*-post, or wooden stake by a small bungee cord. The unit was oriented toward herbaceous vegetation where the most likely avian acoustic activity would occur. Photographs of several installed units are included in Appendix S1.

The goal of acoustic data collection was to count the total number of unique bird species present at each site through manual listening (Buxton et al., 2018; Dixon et al., 2020; Wimmer et al., 2013). The exact range of dates was determined after sampling by examining when successful recordings overlapped. Recordings selected from dawn hours were used in this study because more species per site were identified compared with recordings selected from throughout the day using an acoustic index in Dixon et al. (2020). Each AudioMoth was supplied with sufficient long-term storage (a Secure Digital card) and battery power to follow a recording program for 1 min every 10 min throughout the morning with a sample rate of 48 kHz. June 2019 was selected as the target period for acoustic recording when resident acoustic activity was expected to be greatest and not mixed with migratory species that typically move through the area earlier in the year. The exact start date of acoustic data collection was different for each site and depended on recorder installation. At a minimum, 95 1-min recordings were collected across 6–8 days from approximately 2 h after sunrise (i.e., 5:40–7:40 am local time). For sites with 6 or 7 days of acoustic data collection, the 2-h window of retrieval was increased until 95 recordings were obtained.

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All 1-min recordings were subjected to manual listening and identification of bird species vocalizations. Raven Pro 1.5 software was used as a convenient way to interact with the audio recording and spectrogram. If a species was unknown, it was recorded as such and counted as a unique species. Species were identified at all sites by Adam Patrick Dixon. The greatest overlap in successful recordings, which was defined as at least 6 days of continuous recording, occurred between 19 and 27 June 2019 (Appendix S2: Figure S1). A list of all original recording sites is presented in Appendix S2: Table S1, with successful recordings noted and reasons for sites removed from the analysis provided.

Species area curves (SACs) were used to determine how well the listening effort captured potential VBRICH at each study site. To identify potential changes resulting from greater listening effort (e.g., >95 1-min recordings), estimates of species accumulation were extrapolated to 200 1-min recordings. Self-starting species-area models were used to predict minimum and maximum extrapolated values from 96 to 200 additional recordings. A self-starting nonlinear model fits an asymptotic regression function to specify a rate of decay. Two self-starting models available in the vegan package in R (Oksanen et al., 2007) provided high and low estimates of the decay rate constants. The "SSasymp" function assumes the rate is trending toward an asymptote and was therefore used to estimate the highest rate of decay and a lower overall bound of bird richness with increased listening effort. The "Ssarrhenius" function, on the other hand, estimates a lower rate of decay and so was used to provide an upper bound on species accumulation estimates with increased effort.

VBRICH was categorized into three groupings. The first group was for all birds observed (referred to as VBRICH). The second and third groupings separated grassland birds and nongrassland birds. The VBRICH grassland category is composed of bird species observed that are listed in Vickery et al. (1999) as obligate or facultative grassland bird species in North America. The VBRICH nongrassland category is composed of all other species. These groupings indicate whether the birds observed are adapted to and dependent upon grassland habitat features, or if they were simply ranging and utilize other habitats just as regularly.

Noncrop vegetation area

Local land-cover maps were developed for each sample site to produce a spatial representation of noncrop vegetation using a combination of PlanetScope (PS) four-band cloud-free scenes (3.7 m ground sample distance resampled to 3 m) from the 2019 growing season, National Agricultural Inventory Program (NAIP) four-band data (~1-m resolution) collected across the study region during the June to August 2019 time period, and high-resolution (1 m) topographic data (Appendix S2: Table S3). This process yielded a 1-m spatial resolution land-cover map for each acoustic recording location that was used to quantify total habitat area. Full details of the land-cover classification procedure and validation of the maps are included in Appendix S2.

Noncrop vegetation texture

Habitat quality within noncrop vegetation in Iowa can vary widely from a monoculture of introduced grass species to a species-rich prairie remnant. To account for this, we reasoned that habitat area could be more predictive if it incorporated the additional variables that describe heterogeneity within habitat. Spectral differences within remotely sensed imagery produced by different plant species and vegetation structural heterogeneity represent variation thought to be associated with increased habitat resource availability (Palmer et al., 2002; Stein et al., 2014). The pattern and degree of such spectral differences can be quantified by measures of texture such as the gray-level co-occurrence matrix (GLCM), which computes the frequency of normalized pixel brightness values within an image (Hall-Beyer, 2017). Summaries of image texture at medium and coarse spatial grains have been positively correlated with bird species richness (Culbert et al., 2012; Farwell et al., 2020; St-Louis et al., 2006). Enhanced Vegetation Index (EVI) data from PS imagery from late June 2019, corresponding most closely with acoustic data collection, already utilized for the land-cover classification were used to derive noncrop vegetation texture. GLCM texture was computed from EVI values within an analytical mask of noncrop vegetation using the raster and GLCM packages in R (Hijmans et al., 2015; Zvoleff, 2020). GLCM texture values were calculated using a 3×3 moving window (9×9 m) of four gray levels to maximize the likelihood of pixel value matches (Clausi, 2002). The 3×3 neighborhood was the smallest analytical window that complemented efforts to map fine-grained heterogeneity. GLCM metrics included GLCM variance and GLCM dissimilarity, which were chosen because they were not expected to be correlated. GLCM variance is a descriptive statistic that measures dispersion around the mean of reference and neighbor pixel combinations (Hall-Beyer, 2017). GLCM dissimilarity emphasizes the contrast between adjacent pixels with a weighted matrix that biases wider ranging values (Hall-Beyer, 2017). Final GLCM texture values were averaged within the study area extent and scaled to values between 0 and 1 for interpretability.

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Study area extent and spatial autocorrelation

For measures of species diversity, taxonomically related groups likely respond to similar range of scales (Fahrig, 2013; Martin, 2018). In Dixon et al. (2020), the 100-m spatial extent was found to roughly correspond to the range of acoustic detection using the AudioMoth, representing a physical extent of the acoustic observations, and therefore can be used if no statistically significant difference exists between tested extents. Bird species, however, may respond to landscape heterogeneity greater than 100 m as individuals and species require a larger home range to carry out life cycle functions (Darras et al., 2018; Le Provost et al., 2021). To examine this possibility, an assessment of the spatial extent where the highest correlation was found between noncrop vegetation percentage and VBRICH determined the appropriate spatial extent in subsequent predictive modeling (Jackson & Fahrig, 2015; Lechner et al., 2012). Pearson's correlation of VBRICH and noncrop vegetation percentage was assessed at spatial extents ranging from 100 to 1000 m. Differences between extents were then assessed for a statistically significant difference by calculating a z-score and checking for the two-tailed probability that the scores were different. Site locations were also assessed for spatial independence using Moran's I test. Model residuals and a spatial weights matrix using the geographic coordinates of each sample location were used to calculate a permutation test (1000 permutations) for Moran's I statistic using the spdep package in R (Bivand & Wong, 2018).

Predictive modeling

Noncrop vegetation area percentage and two measures of noncrop vegetation texture (Table 1) served as explanatory variables and were selected based on data exploration including normality and Pearson's correlation analysis. Generalized linear models (GLMs) with a Poisson distribution were specified since the dependent variable was count data and predictor variables were not normally distributed (Table 2, Appendix S2: Figure S5) (Zuur et al., 2009). All statistical analysis was completed in R version 4.1.2. All explanatory model variable combinations were evaluated based on their Akaike's information criterion score adjusted for small sample sizes (AIC_c). Explained deviance and the significance of each predictor provided additional context to the overall interpretation of results. Explained deviance operates similarly to an adjusted R^2 value by providing a measure of variation accounted for by the model (Zuur et al., 2009). Collinearity among independent variables was assessed by a correlation matrix and variance inflation factors (VIFs). Models were also assessed for violation of assumptions to ensure normality of residuals and for undue effect by outliers.

RESULTS

Assessing vocalizing bird richness

A total of 44 sites out of the original 60 deployed were used in the analysis, resulting in a 73% overall data collection success rate. Of the failed data acoustic data collection, four sites

TABLE 1 Variable names, short names, and data inputs used to create variables and variable definitions describing inputs for correlation and regression analyses.

Variable	Short name	Data input	Definition
Vocalizing bird richness	VBRICH	Manual identification from AudioMoth	Total count of unique bird species vocalizations during observation period at each site
Vocalizing grassland bird richness	VBRICH grassland	Manual identification from AudioMoth	Total count of unique grassland bird species vocalizations during observation period at each site (Vickery et al., 1999)
Vocalizing nongrassland bird richness	VBRICH nongrassland	Manual identification from AudioMoth	Total count of unique nongrassland bird species vocalizations during observation period at each site
Noncrop vegetation percentage	NC%	Raster stack of EVI from PlanetScope June to September 2019, 2019 NAIP	Noncrop vegetation percentage within a focal distance of each recorder
Noncrop vegetation texture variance mean	TVAR	EVI from late June 2019 PlanetScope	Average GLCM variance of EVI within a 3×3 window for noncrop vegetation at each site
Noncrop vegetation texture dissimilarity mean	TDISS	EVI from late June 2019 PlanetScope	Average GLCM dissimilarity of EVI within a 3×3 window for noncrop vegetation at each site

Abbreviations: EVI, Enhanced Vegetation Index; GLCM, gray-level co-occurrence matrix; NAIP, National Agricultural Inventory Program.

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TABLE 2 Candidate set of generalized linear models with hypothesis.

Model	Univariate relationship	Multiple variable relationship	Hypothesis
Model 1	Noncrop vegetation %		Noncrop area alone best explains VBRICH
Model 2	Noncrop vegetation texture mean		Noncrop heterogeneity, not area, best explains VBRICH
Model 3		Noncrop vegetation % + Noncrop vegetation texture mean	Noncrop area and heterogeneity jointly explain VBRICH
Model 4		Noncrop vegetation % × Noncrop vegetation texture mean	Noncrop area and heterogeneity interact to explain VBRICH

Abbreviation: VBRICH, vocalizing bird species richness.

(~7% of sites) were managed by Adam Patrick Dixon and 12 (20% of sites) by collaborators. The most common reason for failed data collection was excess moisture from wildlife tampering with the protective plastic bag, leading to nine recorders with less than 6 days of dawn recording. Four sites did not yield data because the collaborator either stopped responding to telephone calls or electronic communications, or they simply did not install the recorder. Two recorders were missing from the sites upon collection.

Manual identification of bird species vocalizations identified 51 species across sites and ranged between seven and 26 vocalizing bird species per site (Figure 3). A total of 17 grassland species and 32 nongrassland species were identified (Appendix S2: Table S2). Species vocalizations that could not be attributed to a species but were distinct were marked as unknown and counted toward the site's unique vocalizations. Unknown species were not attributed to either grassland or nongrassland nesting species but were counted toward the overall VBRICH count. Unknown vocalizations occurred at 38 sites, adding up to two additional species per site to the VBRICH count and were determined to be unique from other species already observed at the site. SACs and extrapolated VBRICH amounts using the maximum extrapolated values were significantly correlated at 0.97, suggesting a similar rank order and similar statistical outcomes regardless of listening effort (Appendix S2: Figures S6 and S7). The difference between total number of species identified when the listening effort was 95 recordings per site and if the listening effort identified all additional species using the maximum extrapolated values suggested that an average of at least 81% of the species present across sites were identified.

Influence of noncrop vegetation on avian species richness

Selection of study area extent

The Pearson's correlation between VBRICH and noncrop vegetation percentage was highest ($r = 0.64$) within 300 m from the acoustic monitoring location, so this was selected as the study area extent (Figure 4). To understand the significance of this finding, noncrop vegetation percentage (NC%) values within 100 m (lowest r) and 300 m of the acoustic monitoring were assessed using the overlapping correlations based on dependent group tests in the cocor package in R (Diedenhofen & Musch, 2015). The two groups of NC% values at each spatial extent were found to be significantly different (Pearson-Filon's $z = -2.1$, p-value $= 0.036$). There was minimal overlap of 300-m landscapes, with the closest acoustic monitoring locations being 295 m apart and second closest locations 447 m apart.

Correlation between variables

Pearson's correlation revealed significant relationships between VBRICH and two measures of noncrop vegetation (Appendix S2: Table S5). Noncrop vegetation percentage was positively correlated ($r = 0.62$, $p < 0.001$) with VBRICH, demonstrating a strong association between habitat area and this measure of avian biodiversity. There was a clear contrast between the two measures of noncrop vegetation texture in relation to VBRICH. The mean noncrop vegetation texture dissimilarity (TDISS) demonstrated no relationship with VBRICH. The mean noncrop vegetation texture variance (TVAR) was positively correlated ($r = 0.40$, $p < 0.01$) with VBRICH.

Modeling results

Data exploration, including the results from the correlation analysis using all variables, were used to compose a set of hypotheses and GLMs (Table 2). TDISS was dropped because there was no apparent relationship with VBRICH in the correlation analysis. The remaining predictors (NC%, TVAR) were tested in single- and multiple-variable configurations with the three sets of VBRICH (all birds, grassland birds, nongrassland birds).

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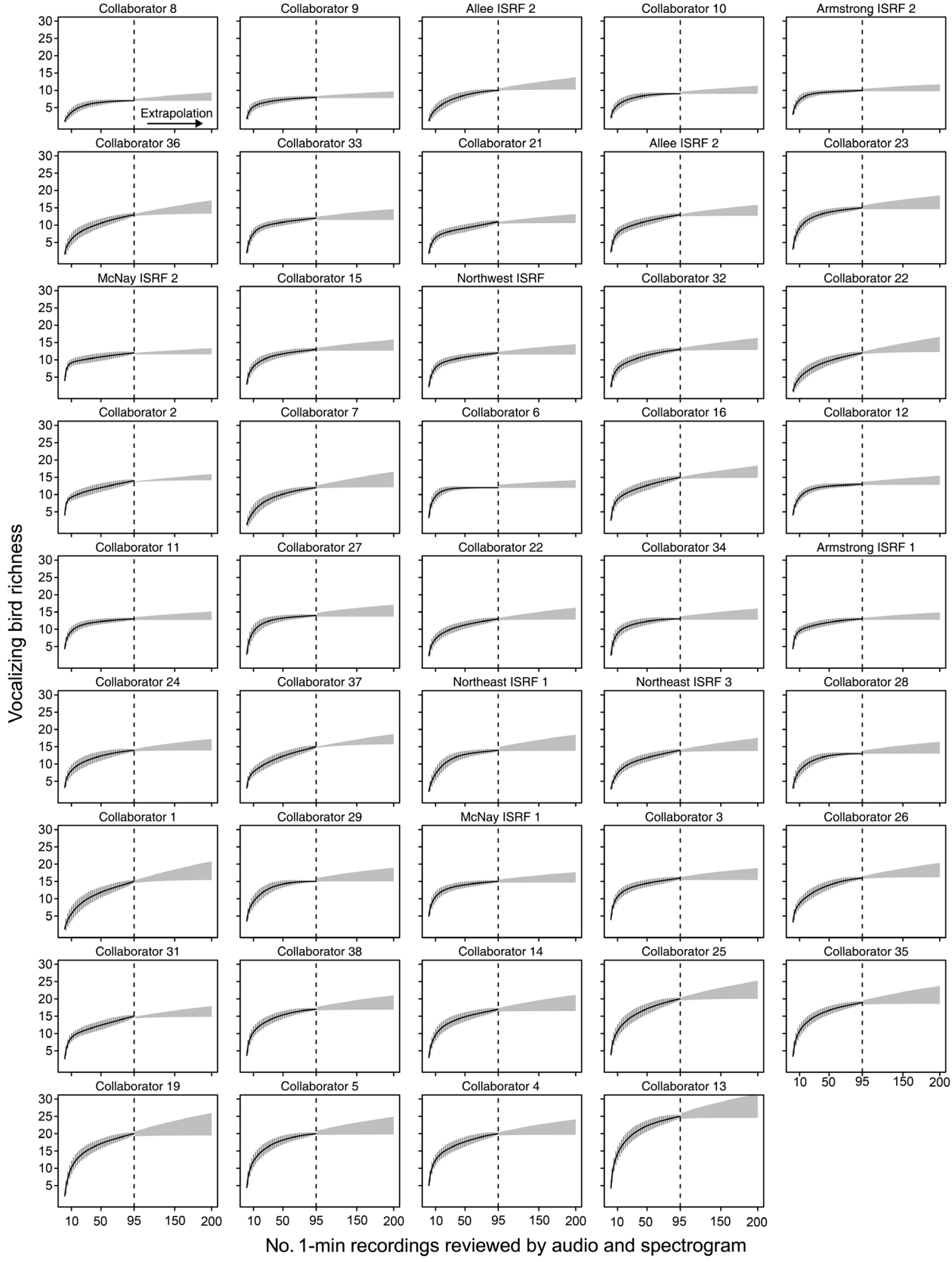

FIGURE 3 Species accumulation curves (SACs) at 44 acoustic recording locations developed from audio and spectrograms of 95 1-min recordings. Hatched lines show SD of SAC values. Shaded gray after vertical dashed line represents hypothetical 96–200 additional recordings and resulting SACs with range of high and low predicted vocalizing bird richness values based on self-starting models, which provided additional examination of how well the listening effort captured the true species richness of vocalizing birds.

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Results demonstrated the most support for the univariate model (Model 1) with NC% explaining VBRICH (Table 3, Figure 5). This model had the lowest AIC_c and higher explained deviance than the univariate model using TVAR to explain VBRICH. These results were similar with VBRICH nongrassland but not with VBRICH grassland, which showed no apparent relationship. Multiple regression models (Models 3 and 4) assessing joint significance as well as interactions between NC% and TVAR failed to demonstrate joint significance or that the effect of either variable was altered by the presence of the other. This result held across all model configurations. TVAR was not significant as an independent variable outside of the univariate model (Model 2), which included an increase in AIC_c and lower explained deviance. The NC% coefficient for log counts in Model 1 was 0.0076. Thus, a 10% increase in noncrop vegetation should increase VBRICH by ~8%.

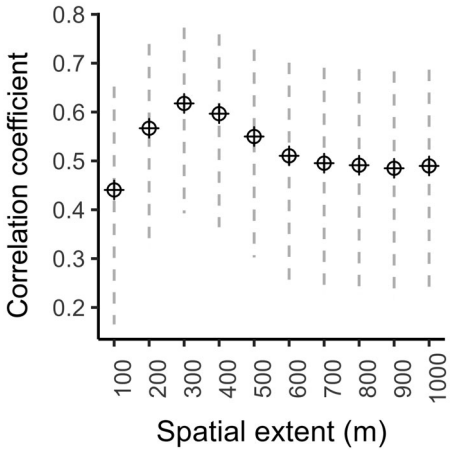

FIGURE 4 Pearson correlation between vocalizing bird richness (VBRICH) and noncrop vegetation percentage ($n = 44$) measured at spatial extents ranging from 100 to 1000 m from the recording location. All values were significant ($p < 0.01$). Error bars show 95% CIs based on Fisher's *r*-to-*z* transformation.

Model diagnostics

Model diagnostics indicated no serious issues. While the NC% and TVAR were significantly correlated ($r = 0.36$), there were no indications of multicollinearity. Model 4 included interaction terms and so predictably had high VIF scores. We also examined model residuals and found no evidence of significant spatial autocorrelation (e.g., VBRICH Model 1—$I = 0.1$, p-value $= 0.053$).

We assessed several alternative models to determine whether timing of observations or presence of outliers influenced results. First, since our set of recordings was derived from a period spanning several weeks (Appendix S1: Figure S1), we examined results when the most recording dates aligned, which was 19 June to 27 June ($n = 32$). We found slightly less statistical power but similar results across models (Appendix S2: Table S6). Second,

TABLE 3 GLM Poisson regression model summary information ($n = 44$) for noncrop vegetation within 300 m of acoustic recorder.

Variables and model statistics	VBRICH				VBRICH grassland				VBRICH non-grassland			
	Model 1	Model 2	Model 3	Model 4	Model 1A	Model 2A	Model 3A	Model 4A	Model 1B	Model 2B	Model 3B	Model 4B
Noncrop percentage	**0.008**		**0.007**	0.001	0.003		0.003	−0.005	**0.013**		**0.012**	0.009
p	0.0004		0.004	0.945	0.241		0.294	0.772	0.00002		0.001	0.696
CI	(0.003, 0.012)		(0.002, 0.011)	(−0.026, 0.028)	(−0.002, 0.009)		(−0.003, 0.010)	(−0.040, 0.029)	(0.007, 0.020)		(0.005, 0.018)	(−0.037, 0.055)
Noncrop texture		**0.455**	0.262	0.174		0.131	0.035	−0.088		**0.990**	0.649	0.608
p		0.022	0.215	0.559		0.601	0.896	0.810		0.004	0.074	0.256
CI		(0.067, 0.843)	(−0.152, 0.675)	(−0.408, 0.756)		(−0.359, 0.620)	(−0.488, 0.559)	(−0.803, 0.627)		(0.322, 1.658)	(−0.062, 1.359)	(−0.439, 1.655)
Noncrop percentage × Noncrop texture				0.008				0.013				0.004
p				0.677				0.626				0.918
CI				(−0.031, 0.048)				(−0.038, 0.063)				(−0.063, 0.070)
AIC_c	221.3	227.5	222.1	224.3	191.3	192.3	193.6	195.8	19.5	197.2	189.5	191.9
Explained deviance	35.5	16.5	4.2	4.8	9.2	1.9	9.3	1.9	29.3	16.6	35.4	35.4

Note: Variables included in model are listed vertically with log count coefficient values. Coefficients are in bold if $p < 0.05$. CIs (95%) and *p*-values are reported under each coefficient. Noncrop texture refers to noncrop vegetation texture variance mean (TVAR) variable. Interacting variables are joined with a ×.

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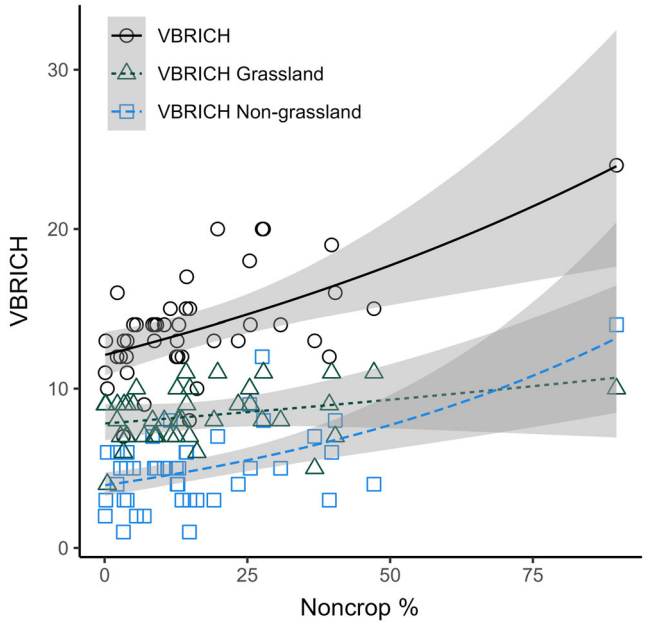

FIGURE 5 Scatterplot of noncrop vegetation percentage (NC%) and vocalizing bird richness (VBRICH), representing all bird species observations, VBRICH grassland, and VBRICH nongrassland with Poisson regression line fit. Shaded area represents 95% CI.

an outlier existed on the site with the highest amount of NC% and VBRICH. Cook's distance indicated that removal of the site was not warranted, nor were any model assumptions violated with its presence, and so it was left in the model. Despite this, we examined the effect on the overall results should the point be excluded and found that the power of statistical associations declined slightly, but that statistical significance with NC% as the predictor remained, as did the directionality of all relationships (Appendix S2: Table S7).

DISCUSSION

Noncrop vegetation and acoustically measured avian species richness

The results of this study provide evidence for a relationship between acoustically measured avian species richness and the area of noncrop vegetation habitat in intensively cropped landscapes. Results are in line with other studies of habitat area explaining animal biodiversity in agricultural landscapes (Burel et al., 2013; Fahrig et al., 2011; Tscharntke et al., 2012). Our analysis provides additional evidence that passive acoustic monitoring has value in determining avian species and habitat relationships in row-crop agricultural landscapes. These results correspond with evidence from a previous study with a similar methodology but with 12 acoustic recording locations rather than the 44 included in the present analysis (Dixon et al., 2020). However, we failed to show that grassland birds were independently significant in our study. This was evidenced by the larger noncrop vegetation coefficient for the VBRICH nongrassland and the lack of significance of explanatory variables in VBRICH grassland models. A potential explanation is that the landscapes we assessed heavily favored low amounts of noncrop vegetation and grassland birds simply require more space and floral resources for nesting and foraging than nongrassland birds in agricultural landscapes. Only one site contained more than 50% noncrop vegetation, and most sites had less than 25% (Appendix S2: Figure S4). Furthermore, some row-crop agricultural practices can make habitat hostile to birds. Herbicides or insecticides can have sublethal effects on bird health through forage quality or physiological damage and result in extirpation from a small habitat over a longer period of time (Stanton et al., 2018). Practices like mowing or tilling can disrupt grassland bird species either through nest destruction or loss of habitat (Shaffer & DeLong, 2019). Periodic management practices are very difficult to measure using remotely sensed data because the timing is different from image capture dates and/or the spectral signature is difficult to detect (Vasseur et al., 2013). Comprehensive field-level surveys that document these practices on a per farmer basis may be the best way to incorporate impacts of agricultural practices on habitat.

Noncrop vegetation texture

In Iowa, herbaceous noncrop vegetation composition and structure vary widely. Capturing these characteristics in maps of noncrop vegetation could prove valuable. While we did demonstrate the value of habitat area in explaining VBRICH (Model 1), we failed to show that model performance was improved when NC% and TVAR were jointly considered or as interacting variables (Models 3 and 4). We also found, when considered as separate univariate models, that model performance decreased (measured as AIC_c) under TVAR (Model 2). These results and the lack of joint significance indicate that texture as measured may not be completely independent of NC%. While collinearity was not an issue, we did find that NC% and TVAR were significantly correlated at $R = 0.36$. This pattern of correlation, as well as that lack of improvement in model results (Models 3 and 4) when considered jointly or through interactions, implies shared variance of TVAR and NC% in explaining VBRICH. This was an interesting result because previous studies showed that texture measures

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quantified in a similar manner using 30-m-resolution data did significantly explain avian species richness patterns over broad scales (Culbert et al., 2012; Farwell et al., 2020), although these studies only measured texture and did not include measures of habitat area in their research design. Therefore, our results align with those previous efforts since texture did significantly explain VBRICH in Model 2. On the other hand, our results did not show that our measure of texture added value to habitat area as the best way to explain VBRICH. This could have been due to our examination of only noncrop vegetation texture and not of spectral heterogeneity across the whole row-crop landscape. We were essentially comparing two measures of the same object (noncrop vegetation). Another reason could have been that even at 3-m resolution, texture analysis fails to sufficiently describe variation in the structural and compositional heterogeneity of noncrop vegetation and that higher-resolution data would have more value.

Our exploration of habitat heterogeneity was not exhaustive. Future research could incorporate other measures of spectral diversity of avian habitat and combine the information with direct measures of herbaceous noncrop plant species diversity and structure (Gholizadeh et al., 2019). Land-cover classifications across regions are difficult to create with high-resolution data because of the degree of variation in reflectance values over small areas. Measures of image texture could be useful as it effectively normalizes remotely sensed heterogeneity across multiple sites with different atmospheric conditions at time of capture. The methods used to characterize texture as a heterogeneity proxy ultimately need to be refined and perhaps compared to field-verified heterogeneity data to assess their validity independently of NC%.

Effectiveness of passive acoustic monitoring

Forty-four out of the 60 sites initially established produced usable data. This was a success rate of 73%. Moisture was the biggest factor in recorder failure, which was often the result of wildlife tampering (likely birds or deer) puncturing the bag either by poking or chewing. The places most likely to experience recorder failure also had more potential habitat (qualitatively assessed), with the practical effect of decreasing observations in areas that would have supplemented data points in the higher noncrop vegetation gradient of this analysis. This likely led to a dampening effect on the statistical power of the final models. Use of a waterproof case would undoubtedly raise the success rate closer to 100%, although monitoring costs would increase. An additional caveat regarding the passive acoustic monitoring results is that the installations of the recorders themselves provided new perching locations for birds at each study site. This may have had the effect of biasing perching bird species, which was not accounted for in any of the data collected. Future research should examine the possibility of placing recorders on the ground or in some manner that does not introduce new habitat structure to the site.

The techniques developed here show potential to increase collaborative biodiversity monitoring across agricultural regions. In total, 22 farmers and land managers participated in acoustic data collection, either through personally collecting the data or by providing access to study site locations. Acoustic information could be highly informative to individual famers, policymakers, and agency staff and would help bridge the experiential divide between researcher and land manager.

Future applications and recommendations

Automated observation methods will likely become easier and less costly, expanding the research questions that can be asked in working lands. The time required to make and evaluate recordings of birds and other wildlife will undoubtedly decrease as automated techniques continue to evolve and improve using low-cost recorders such as AudioMoths and analyzed using the BirdNET analyzer application in the Raven Lite or Kaleidoscope Pro software applications (Kitzes & Schricker, 2019; Manzano-Rubio et al., 2022). State and federal wildlife agencies may utilize this research experience to develop their own monitoring platforms that integrate agricultural operators into their research design and increase the number of observations possible. This could build social capital and create agency among farmers and result in improved wildlife habitat management (MacPhail & Colla, 2020).

Despite our success in establishing a set of research sites, we acknowledge the sample design was a source of potential bias. Convenience-based sampling is quite common in ecological research due to the ease of accessing sample sites, such as roadsides, and is often justified based on logistical grounds (Corn, 2010). For example, the North American Breeding Bird Survey is entirely based on sampling from roadways (Sauer et al., 2003; Scholtz et al., 2017). Achieving a sample design across privately owned lands can require substantial time and effort for the relationship and trust building required to conduct regional-scale research.

Researchers can expand on the types of questions they can ask as the burden of wildlife data collection decreases (Sugai et al., 2019). Qualitative and quantitative data could be produced based on the response of

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agricultural operators to the biodiversity data that were collected on their operation. Ecological and social data about behaviors can be leveraged to investigate how land management leads to different wildlife outcomes (Dixon et al., 2022; Prokopy et al., 2019; Upadhaya et al., 2021).

CONCLUSION

Landscape observation methods enabling increased observations for birds and habitat could assist wildlife conservation efforts in working lands. We investigated scalable methods for fine-grained mapping of noncrop vegetation and acoustic monitoring of birds in landscapes dominated by row-crop agriculture. Significant relationships between VBRICH and noncrop vegetation habitat area were established through a sample of study sites across a large region of Iowa farmland. When limited to only grassland VBRICH, we found no evidence of a relationship with noncrop habitat area. Measures of noncrop vegetation texture representing habitat heterogeneity were not found to add value to habitat area. Results suggest row crop habitats lack the resources needed to harbor grassland bird species. Additional research is needed to develop passive methods able to detect the unique habitat requirements of grassland birds in row-crop landscapes.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data and code (Dixon, 2023) are available in Zenodo at https://doi.org/10.5281/zenodo.7826065. The geographic coordinates of each acoustic recorder location are sensitive and have been removed from the data set; qualified researchers may contact the corresponding author for access to the geographic coordinate data.

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SUPPORTING INFORMATION

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

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