

RESEARCH ARTICLE

Ecovoltaic solar energy development can promote grassland bird communities

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Abstract

1. Ecologically informed photovoltaic (PV) developments that co-prioritize PV electricity generation with ecosystem function ('ecovoltaics') have emerged as a promising land sharing strategy to minimize ecological conflicts associated with PV solar energy development. While habitat-focused ecovoltaic designs can conceptually benefit biodiversity by offsetting or enhancing impacts of PV development, foundational field research is needed to examine how wildlife respond to these novel ecosystems.
2. We conducted passive acoustic monitoring (PAM) in 2023 and 2024 at 13 solar facilities and paired control sites to investigate avian community responses to ecovoltaic facilities in the Midwestern United States.
3. Compared to control sites (row crop agricultural fields), we found that ecovoltaic sites supported more grassland bird species throughout a 17-week monitoring period between May and September. Grassland bird communities on ecovoltaic sites were also more stable than on agricultural controls, as measured by the Jaccard dissimilarity index.
4. We also used PAM-based weekly species occurrences in an occupancy-modelling framework to investigate the influence of PV development and other landscape variables on grassland bird occupancy. 10 out of 13 modelled grassland bird species had greater predicted occupancy probabilities (ψ) on PV sites than control sites.
5. *Synthesis and applications.* Our findings suggest that properly sited and developed ecovoltaic solar facilities in human altered landscapes can improve habitat for birds and other wildlife, but further research is needed to understand which species may benefit most from these novel ecosystems.

KEYWORDS

biodiversity, ecology, habitat restoration, renewable energy, solar energy, sustainable development

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1 | INTRODUCTION

The 21st century has experienced a shift in global energy production, driven by international priorities for sustainable solutions to energy security and to address climate change (Wehbi, 2024). Solar energy has emerged as a leading source of electricity to define this transition, due in large part to declining costs its long-term environmental sustainability (Nijse et al., 2023). Photovoltaic (PV) solar electricity generation could become the dominant global renewable energy source by 2030 (IEA, 2024). By 2050, the United States (U.S.) alone could install up to 1 terawatt (TW) of large-scale ground-mounted PV solar energy (DOE, 2021). This energy future will require a 10x increase in existing ground-mounted PV solar deployment in the U.S. over the next two decades (EIA, 2025).

The future build-out of large-scale PV developments will require considerable amounts of land (DOE, 2021; Walston et al., 2021). As such, land use trade-offs rank among the most important considerations influencing widespread PV deployment. For example, PV solar energy development in rural landscapes can result in loss of farmland (Goldberg, 2023; Sorensen et al., 2022). Dual land use designs can alleviate these impacts by allowing PV solar development to occur with other compatible land uses. Under this approach, the concept of 'ecovoltaics' has emerged as a land sharing strategy that co-prioritizes PV energy production with ecosystem function (Sturchio & Knapp, 2023). Opposed to turfgrass management, a conventional vegetation practice at many PV installations, ecovoltaic designs can improve ecosystem function through onsite habitat establishment (Sturchio et al., 2024; Walston et al., 2021).

A major concern around PV solar energy deployment is the impact on biodiversity. Construction and operation of PV solar installations can negatively impact biodiversity through habitat loss and various forms of direct and indirect mortality (e.g. collision-related mortality) (Gómez-Catasús et al., 2024; Karban et al., 2024). However, impacts are context-dependent and there is emerging evidence suggesting that PV solar installations could provide a net benefit for biodiversity under certain siting and management configurations (Treasure et al., 2024). In the Midwestern U.S., most PV facilities are sited on former arable croplands such as corn and soybean fields (Sorensen et al., 2022; Walston et al., 2021). Conceptually, the conversion of row crop agriculture to ecovoltaic solar energy developments represents a land use change that can enhance the site's ecological value by stabilizing soils, restoring native vegetation and improving wildlife habitat for foraging, breeding and nesting and refuge (Sturchio et al., 2025; Szoldatits et al., 2025; Tölgyesi et al., 2023). For example, recent studies have demonstrated relatively rapid increases in insect community abundance in response to native grasses and forbs established at ecovoltaic sites sited on former agricultural lands (Blaydes et al., 2024; McCall et al., 2024; Walston et al., 2024).

While the positive responses of plant and insect communities show promise for ecovoltaic designs, evaluating responses at higher trophic levels is necessary to more comprehensively understand the effects of these novel land use configurations on biodiversity. Birds

are important bioindicators of ecosystem well-being (Rosenberg et al., 2019) and could be influenced by changes in habitat composition and prey abundance (e.g. insects) resulting from PV solar energy developments. Recent studies in Europe have shown greater bird abundance and diversity on PV solar sites than agricultural control sites representative of pre-solar land uses (Copping et al., 2025; Golawski et al., 2025; Jarčuška et al., 2024). However, outside the desert Southwest (e.g. Kosciuch et al., 2021), there has been little research on bird community responses to PV solar in the U.S.

North American grassland bird populations have declined substantially in recent decades, primarily due to anthropogenic habitat loss such as agricultural expansion (Johnson et al., 2019). Thus, there is a unique opportunity for ecovoltaic solar developments on former agricultural fields in these landscapes to support grassland bird species by offsetting habitat losses. In this study, we used passive acoustic monitoring (PAM) data to examine grassland bird community responses to ecovoltaic sites in the Midwestern U.S. PAM has become a popular wildlife monitoring tool for ecologists and natural resource managers (e.g. Bielski et al., 2024; Hack et al., 2024; Schuster et al., 2024; Wood et al., 2024), due in large part to advancements in artificial intelligence to improve species call recognition (e.g. BirdNET (Kahl et al., 2021)). In some cases, automated species detection approaches using PAM can outperform more traditional point count survey methods of estimating avian species richness (Darras et al., 2018; Schuster et al., 2024). Some advantages of PAM over manual survey methods include the ability to continuously monitor multiple locations over long time periods, minimization of human disturbances and biases in the monitoring design, and the ability to monitor cryptic species or in complex environments where views can be obstructed (Kahl et al., 2021; Schuster et al., 2024; Sugai et al., 2019). We used PAM to examine avifauna responses to ecovoltaic solar sites by investigating whether grassland bird species richness, diversity and occupancy on ecovoltaic sites differed from offsite agricultural control sites.

2 | METHODS

2.1 | Study area

Our study included 13 PV solar facilities and 12 control sites across 5 Midwestern U.S. states (Figure 1). The PV sites ranged in size between 7.5 and 550ha with nameplate electric generation capacities between 3.5 and 200MW (Table 1). The previous land use of all sites prior to conversion to PV solar installations was row crop agricultural production (e.g. corn, soybeans). Throughout the study, agricultural production remained the dominant land use in the regions surrounding the solar sites.

Construction of the PV solar facilities was completed between 2015 and 2021 (Table 1) and the 'age' of each solar facility (number of years in operation) ranged between 2 and 8 years at the time of monitoring (average: 4 years). Most of the PV facilities consisted of single-axis tracking technologies ($n = 10$), which allowed the PV

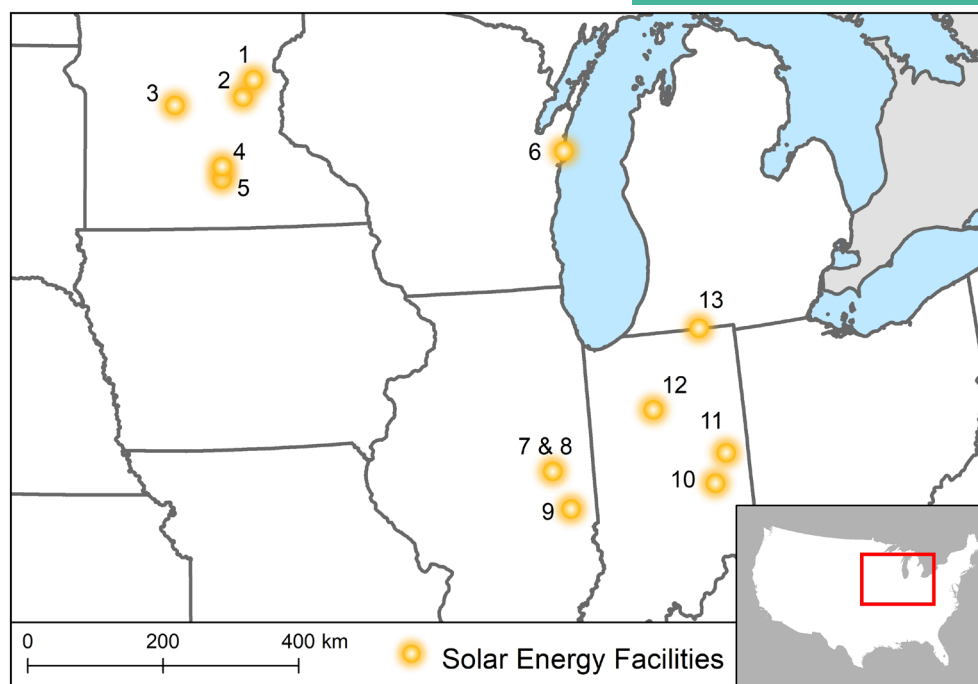


FIGURE 1 Map of solar sites in the Midwestern United States examined in this study. Solar site numbers correspond to the numbers listed in [Table 1](#).

TABLE 1 Attributes of the 13 solar sites monitored in this study.

Solar site number ^a	Solar facility size ^b	Year construction and seeding complete	Year(s) surveyed	Percent of site managed for habitat	Number of on-site survey locations
1	13.5 ha (5 MW)	2018	2024	100%	1
2	7.5 ha (3.5 MW)	2018	2023	100%	1
3	14 ha (4 MW)	2018	2023	100%	1
4	16.5 ha (4.5 MW)	2018	2024	100%	1
5	16.9 ha (5.5 MW)	2018	2023	100%	1
6	188 ha (100 MW)	2021	2024	10%	2
7 ^c	8 ha (4.7 MW)	2015	2024	0%	1
8	21.5 ha (12 MW)	2021	2024	100%	1
9	550 ha (200 MW)	2021	2024	10%	1
10	385 ha (173 MW)	2021	2024	5%	2
11	485 ha (200 MW)	2021	2024	8%	2
12	19 ha (10 MW)	2021	2023	100%	1
13	34.5 ha (19 MW)	2020	2024	100%	1

^aSolar site number corresponds to the numbers in [Figure 1](#).

^bThe size in ha represents the total footprint size of the fenced perimeter. Parentheses represent the nameplate capacity in MW AC.

^cSite #7 was not an ecovoltaic site. 100% of the onsite vegetation at this site was turfgrass.

panels to rotate throughout the day to maximize sun exposure, whereas some of the sites utilized fixed-tilt PV panels ($n=3$). After construction, the PV sites were planted with seed mixes consisting of grasses and forbs. Portions of most PV sites ($n=12$) were planted with seed mixes consisting of native and naturalized perennial flowering vegetation. These habitat-focused seed mixes

were intentionally planted at the sites to improve soil health and enhance wildlife habitat. The entire footprint of smaller PV facilities (<100 ha) was seeded with the habitat-focused seed mix. At the larger PV facilities (≥ 100 ha), the habitat-focused seed mix was planted between 5% and 10% of the entire site ([Table 1](#)). The remaining areas at these larger sites were managed for turfgrass or

livestock grazing. There was one PV site that was not planted with a habitat-focused seed mix (Table 1, solar site number 7); the sole vegetation cover at this site was turfgrass. There was considerable variability in the habitat-focused seed mixes planted at each ecovoltaic site, but the dominant native species planted across the sites included Aster species (*Symphyotrichum* spp.), Black-eyed Susan (*Rudbeckia hirta*), Coneflower species (*Echinacea* spp.), Milkweed species (*Asclepias* spp.) and Partridge Pea (*Chamaecrista fasciculata*). See McCall et al. (2024) for example seed mixes planted at some of the sites. Vegetation management at all sites consisted of early season mowing and occasional as-needed control of invasive species and woody vegetation (e.g. localized herbicide treatments to control non-native Canada Thistle [*Cirsium arvense*]).

2.2 | Survey design

The larger PV sites (≥ 100 ha) were made up of several disjunct fenced PV arrays, each one usually being between 10 and 25 ha in size. Despite aggregate differences in PV facility size, the size of individual fenced footprints of all sites was approximately the same. We established at least one monitoring location at each PV site, positioning the survey point near the onsite habitat area, if available. At some of the larger sites (≥ 100 ha), we included one or two additional survey locations (Table 1). These additional monitoring locations were placed in turfgrass or grazing-dominated areas of the PV site.

We identified paired control sites in the region around each PV facility. The conversion of row crop agriculture to PV solar development is a growing form of land use change in the Midwestern U.S. (Sorensen et al., 2022; Sturchio et al., 2025; Walston et al., 2021). All PV sites in this study were previously used for crop production in the years immediately before conversion to PV development. Therefore, we selected row crop agricultural fields (corn and soybean fields) as control sites to represent the land use prior to PV development (Figure 2). All row crop control sites were between 10 and 40 ha in size, which approximated the sizes of the PV fenced perimeters. Two solar facilities that were separated by 1 km (sites #7 and #8; Figure 1) shared a single control location. Control survey sites were adjacent to active crop fields (corn or soybeans). We identified monitoring locations in control areas along fence lines or narrow grass-dominated swales that bordered these crop fields. We ensured all control-monitoring locations were >100 m from major human developments such as roadways or residential structures (see Figure 2 for an example). Using this design, arable lands comprised $>80\%$ of the area within 100 m of all control monitoring locations. All monitoring locations at control sites were at least 200 m from the nearest PV facility border (range: 200–1500 m) and ≥ 500 m from the nearest monitoring location. In total, there were 28 unique monitoring locations: 16 locations on the solar facilities and 12 control sites.

2.3 | Passive acoustic monitoring

We conducted passive acoustic monitoring at the PV sites and control sites from May to September in 2023 and 2024. This study was part of a broader regional effort to investigate biodiversity responses to PV development; therefore, our study sites and monitoring methods were similar to previous studies (e.g. Szoldatits et al., 2025). Autonomous recording units (ARUs; Wildlife Acoustics Song Meter Mini, Maynard, MA, USA) were installed at each survey location. We mounted ARUs on metal tripods or posts raised approximately 2 m above ground. We programmed the ARUs to record 16-bit WAV audio at a sample rate of 24,000 Hz and default gain settings (18 dB) for 4 h per day: 2 h around sunrise and 2 h around sunset. We consistently monitored sites in pairs by simultaneously deploying ARUs on the PV sites and the paired control sites using the same ARU configurations. ARUs were inspected in the field every 2–4 weeks to replace batteries and digital data storage. Based on in situ testing and results from previous studies (Bielski et al., 2024; Darras et al., 2018), we determined the detection range of the ARUs to be 50–100 m for most grassland bird species. To give us confidence that detected bird species were recorded on the PV site, therefore, we placed all onsite ARUs >50 m, and usually >100 m, interior from the PV facility's fenced edge. All but three onsite ARUs were >100 m interior from the PV facility edge. All ARUs were separated by ≥ 500 m (Figure 2).

We analysed the recorded acoustic files with the BirdNET algorithm, a deep artificial neural network capable of identifying over 6000 bird species based on their vocalizations (Version 2.4; Kahl et al., 2021). We configured BirdNET to make species predictions based on weekly eBird (Wood et al., 2011) checklists for the geographic area near each survey location. We used default BirdNET parameter settings for the minimum confidence threshold, sensitivity and overlap. All BirdNET results were saved as tab-delimited data tables.

We evaluated BirdNET performance by generating precision estimates for a subset of focal grassland bird species using methods similar to Walston, Cacho, et al. (2025). We first randomly selected 100 BirdNET-generated detections for each grassland species, equally stratified across the following confidence intervals: 0.50–0.59; 0.60–0.69; 0.70–0.79; 0.80–0.89; and ≥ 0.90 . All sample recordings corresponding to these detections were manually reviewed by trained biologists to determine BirdNET precision, as follows:

$$\frac{\text{True positives}}{\text{True positives} + \text{False positives}}.$$

A true positive detection occurred when an observer confirmed a species was also detected by BirdNET. A false positive detection occurred when BirdNET detected a species that was not confirmed by the observer. We then modelled precision estimates across confidence intervals with linear or logistic functions. We determined species-specific confidence thresholds (SSCT) as the confidence level beyond which precision was consistently ≥ 0.90 . If BirdNET failed to reach this precision level, we removed that species from further consideration for this study. For all remaining grassland species, we used the SSCT to filter

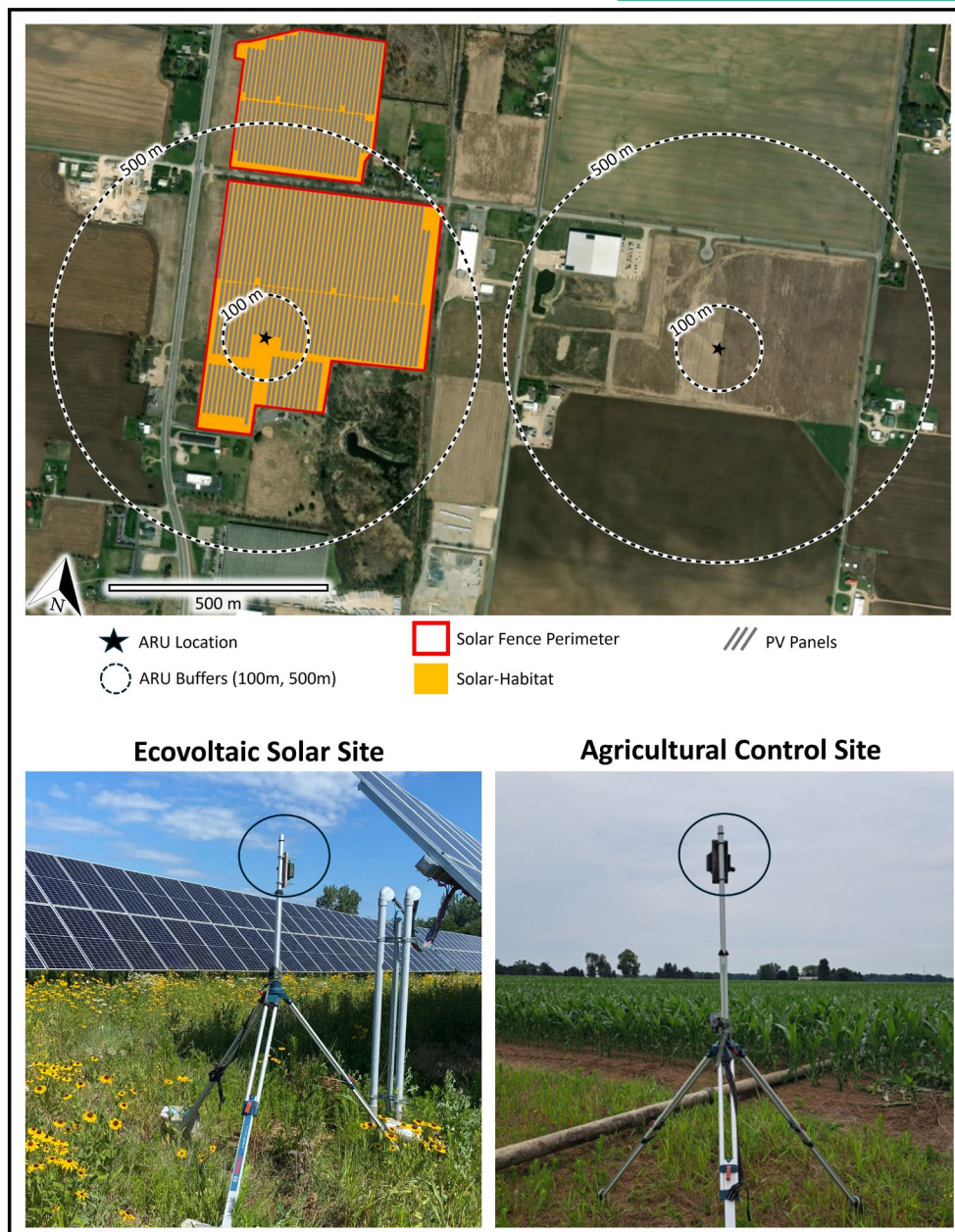


FIGURE 2 ARU monitoring design at an example ecovoltaic site and paired offsite control site. The ARUs are circled in the bottom images. Basemap imagery created using ESRI ArcGIS Pro v3.2. Source of satellite imagery: ESRI, Maxar, Earthstar Geographics and the GIS User Community. Photo credit: L. Walston, Argonne National Laboratory.

all BirdNET detections and we assumed these filtered detections to be valid. This method is similar to other statistical methods to determine SSCT (e.g. Bielski et al., 2024; Hack et al., 2024; Walston, Cacho, et al., 2025; Wood & Kahl, 2024). We used the packages 'dplyr' and 'av' in R version 4.4.1 to organize BirdNET detection tables and review acoustic files.

2.4 | Site and landscape covariates

We mapped and measured six site-level and seven landscape-level variables at each ARU location. The site-level attributes included

ARU location (solar or control site), age of the PV facility at the time of the survey, total size of the solar site (ha), distance from ARU to nearest PV facility edge, year of the survey and latitude. At the landscape level, we measured the proportion of the following variables at 100 and 500-m spatial scales around each ARU location: solar habitat (Habitat100, Habitat500), PV panels (PV100, PV500), grassland (Grass100, Grass500), trees (Tree100, Tree500), agriculture (Ag100, Ag500), water (Water100, Water500) and non-PV developed area such as roads and residential properties (Dev100, Dev500). We used ArcGIS Pro v3.2 (ESRI, Redlands California, USA) and the integrated online satellite imagery base-maps to manually digitize landscape features at both spatial scales.

2.5 | Species richness

Using the SSCT, we determined daily grassland bird species detections for each ARU, using grassland bird species identified in Rosenberg et al. (2019) and MacDonald et al. (2024). We then organized the data to compare species richness between ecovoltaic sites and control areas by week. Our focus was on determining whether species richness near habitat-managed areas of ecovoltaic sites differed from control areas. For this reason, we only included ARUs from the ecovoltaic solar sites that were positioned in or adjacent to the onsite habitat-managed areas. This resulted in 12 pairs of ARUs from solar facilities and control locations. Inconsistent and unbalanced data collection between pairs of ARUs could bias the calculations and comparisons of species richness. To account for this potential bias, we first filtered the paired daily BirdNET detections to dates in which the paired ARUs collected complete days of acoustic recordings. We calculated weekly grassland species richness from this subset of paired detections if there were ≥ 5 matching days of complete recordings each week. Species richness was calculated as the sum of all unique grassland species detected at the SSCT.

From the weekly detections, we estimated grassland bird beta (β) diversity by calculating a Jaccard dissimilarity matrix using the 'vegan' package in R. We calculated weekly dissimilarity values at each ARU location based on the total number of grassland species detected at that location throughout the 17-week monitoring period. Jaccard dissimilarity is calculated as an index between 0 and 1, with greater weekly dissimilarity values closer to 1 indicating greater instability in the grassland bird community due to species turnover and nestedness (Baselga, 2012).

2.6 | Statistical analyses

Statistical analyses were performed in R version 4.4.1 (R Core Team, 2024). We modelled weekly grassland species richness and community dissimilarity by ARU site and landscape covariates with generalized additive mixed models (GAMM) using the 'mgcv' package. GAMMs have emerged as effective methods to understand complex nonlinear ecological relationships and can sometimes outperform linear models (Heit et al., 2024; Szoldatits et al., 2025). We began by examining the individual effects of each site and landscape covariate, using week, site and monitoring year as random effects. From this first step, we found that Ag100, Habitat500 and ARU location (solar or control site) were the three strongest single predictors of grassland species richness (adjusted R^2 : 0.504–0.538; deviance explained: 51.4%–54.1%). PV500, Ag500 and Location were the three strongest predictors of community dissimilarity (adjusted R^2 : 0.486–0.596; deviance explained: 50.7%–61.7%).

We investigated multicollinearity among the site and landscape covariates with pairwise Pearson correlation coefficients and variance inflation factors (VIF). First, we identified strongly correlated pairs of covariates (Pearson $r \geq 0.80$). From these highly correlated pairs, we

kept the one variable that explained the greater variance in grassland bird species richness or community dissimilarity. Due to the strong collinearity between Habitat100 and ARU location (Pearson $r > 0.90$), we did not include both predictors in the same model. Rather, we developed models that used ARU location as a surrogate for solar habitat.

We calculated VIFs with the remaining variables. Severe multicollinearity occurs among variables at VIF values ≥ 10 (James et al., 2013). Working backwards, we calculated VIF of all remaining site and landscape covariates and incrementally removed the ones with VIF ≥ 10 until all remaining variables had VIF < 10 . With these remaining covariates, we constructed GAMMs in a stepwise fashion beginning with null and simple linear models and incrementally added covariates in progressively more complex models.

We were primarily interested in the effect of ARU location on the temporal patterns in species richness and dissimilarity. Therefore, all GAMMs (except the null and simple linear models), included ARU location as a parametric factor and week as a smoothed term. Site identity and monitoring year were considered random effects. The remaining landscape covariates were added as smoothed predictors using cyclic cubic regression splines, which are GAMM splines commonly used to model temporal effects (Pedersen et al., 2019). To keep the number of models manageable, the only interactions considered were between ARU location and week.

We used the `gam.check()` function to assess the fitness of each model, inspect residuals and explore the effects of different knots (k , the smoothing parameter). We used $k=4$ for all smoothed predictors, which allowed for some complexity in the relationships while also avoiding model overfitting (Kosicki, 2020). We fit species richness GAMMs using negative binomial distributions and community dissimilarity GAMMs with Gaussian distributions (using 'log' link in all cases). We tested the normality of residuals for the final models using Shapiro–Wilk tests. For each model, we calculated Akaike information criterion values adjusted for small sample sizes (AICc). After developing the suite of candidate models for each response variable, we determined the best-performing model as the most parsimonious model within $\Delta AICc \leq 2$ from the model with the lowest AICc. We used the adjusted R^2 to consider the relative amount of information explained by each model.

2.7 | Grassland bird occupancy

We estimated single species, single season occupancy (ψ) and detection probability (p) parameters for grassland bird species with the unmarked package in R (Fiske & Chandler, 2011). We calculated weekly occurrences of each grassland bird species at the 28 ARU locations if there was at least one valid detection (based on SSCT) within a week. We calculated weekly occurrences or non-detections only for weeks in which there were ≥ 5 days of recordings. Because occupancy models account for imperfect and unbalanced detections, we did not subset occurrence data to matching days as we did for the GAMMs for species richness and community dissimilarity.

We checked the naïve occupancy for each species and omitted species that occurred at fewer than 10 sites from our occupancy models. For remaining species, we started by creating a null model to represent equal probability of detection and occupancy across all sites and weeks. Because our primary focus was to investigate the effects of solar sites on grassland bird occupancy, all parameterized models included survey location (solar or control site) as detection and occupancy covariates. Survey location and week were the only covariates we used to examine detection probability (p). We first centred and scaled each landscape covariate around zero and added each one incrementally to examine the effects of landscape covariates on site occupancy probability (ψ). We assessed model fit using AIC values, ranking and comparing models based on AIC relative differences between the top ranked model and each other model (ΔAIC). We considered models with $\Delta AIC < 2$ to be substantially supported (Burnham & Anderson, 2002); therefore, we selected the final model as the most parsimonious parameterized model within $\Delta AIC \leq 2$ from the model with the lowest AICc. Model comparisons for all GAMM and occupancy analyses are provided in Supplement S2. Based on the passive nature of our study design, our study did not require ethical approvals. All necessary site access permissions were granted prior to field work.

3 | RESULTS

We collected over 11,000 h of acoustic recordings across all 28 ARU locations between 1 May and 30 September in 2023 and 2024. BirdNET made over 1,300,000 species detections from these recordings at a

confidence level ≥ 0.50 . The three most frequently detected grassland bird species across all sites and years were Dickcissel (*Spiza americana*), Horned Lark (*Eremophila alpestris*) and Eastern Meadowlark (*Sturnella magna*) (Table 2). From all BirdNET detections, we identified 16 grassland bird species, which were detected 646,432 times (nearly 50% of all BirdNET detections). Most of these species were from the Orders Passeriformes (87.5%), but they also included two game bird species (Galliformes; 12.5%). Species-specific precision estimates and SSCT calculations are provided in Figure S1-1.

3.1 | Site and landscape covariates

Several site and landscape covariates were dropped from analyses due to multicollinearity. Site size, distance to PV edge and site age were all highly correlated with other covariates (Pearson $r \geq 0.80$); these covariates were omitted from all analyses (see Figure S2-2 for the covariate correlation matrix). Additionally, the proportion of PV coverage at both spatial scales (PV100, PV500) was removed from all analyses due to high VIF. We retained seven site and landscape covariates that all had VIF < 10 : ARU location, Year, Latitude, Grass500, Ag500, Tree500 and Water500.

3.2 | Grassland bird species richness

The best-performing GAMM to predict grassland bird species richness showed significant positive effects of solar site location

TABLE 2 Summary of the 16 grassland bird species evaluated in this study, in alphabetical order by common name.^a

Scientific name	Common name	Order	Species-specific confidence threshold (SSCT) ^b	Total valid detections at SSCT
<i>Spizella passerina</i>	Chipping Sparrow	Passeriformes	0.900	522
<i>Spizella pallida</i>	Clay-coloured Sparrow	Passeriformes	0.800	4003
<i>Spiza americana</i>	Dickcissel	Passeriformes	0.500	247,037
<i>Sialia sialis</i>	Eastern Bluebird	Passeriformes	0.850	5258
<i>Tyrannus tyrannus</i>	Eastern Kingbird	Passeriformes	0.500	30,453
<i>Sturnella magna</i>	Eastern Meadowlark	Passeriformes	0.800	43,630
<i>Spizella pusilla</i>	Field Sparrow	Passeriformes	0.700	21,828
<i>Ammodramus savannarum</i>	Grasshopper Sparrow	Passeriformes	0.800	36,691
<i>Eremophila alpestris</i>	Horned Lark	Passeriformes	0.500	157,283
<i>Colinus virginianus</i>	Northern Bobwhite	Galliformes	0.500	19,550
<i>Agelaius phoeniceus</i>	Red-winged Blackbird	Passeriformes	0.500	3511
<i>Phasianus colchicus</i>	Ring-necked Pheasant	Galliformes	0.600	1490
<i>Passerculus sandwichensis</i>	Savannah Sparrow	Passeriformes	0.500	64,658
<i>Cistothorus stellaris</i>	Sedge Wren	Passeriformes	0.700	475
<i>Melospiza georgiana</i>	Swamp Sparrow	Passeriformes	0.900	294
<i>Pooecetes gramineus</i>	Vesper Sparrow	Passeriformes	0.850	9749

^aGrassland species based on MacDonald et al. (2024) and Rosenberg et al. (2019).

^bSpecies-specific confidence threshold (SSCT) determined based on BirdNET precision estimates. See Figure S1-1, for species-specific BirdNET precision graphs.

TABLE 3 Summary output for the best-performing generalized additive mixed models (GAMMs) that were fit for grassland bird species richness and grassland bird community dissimilarity.^a

Response variable	Formula (family: Negative binomial, link: Identity) ^b	R ² (adj.)
Grassland bird species richness	Location*** + s(Week)*** + s(Week, Location)** + s(Ag500)* + s(Site ['re'])* + s(Year['re'])***	0.624
Grassland bird community dissimilarity	Location*** + s(Week)* + s(Week, Location)*** + s(Ag500) + s(Habitat500)*** + s(Tree500)*** + s(Water500)*** + s(Latitude) + s(Site ['re'])* + s(Year ['re'])	0.614

^aBased on a comparison of AICc. See supplemental material for model comparisons and results.

^bBest-performing models used cyclic cubic regression splines (bs = 'cc') for all smoothed parameters, with knots equal to 4. 're' = random effect; Significance of each parameter is as follows: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

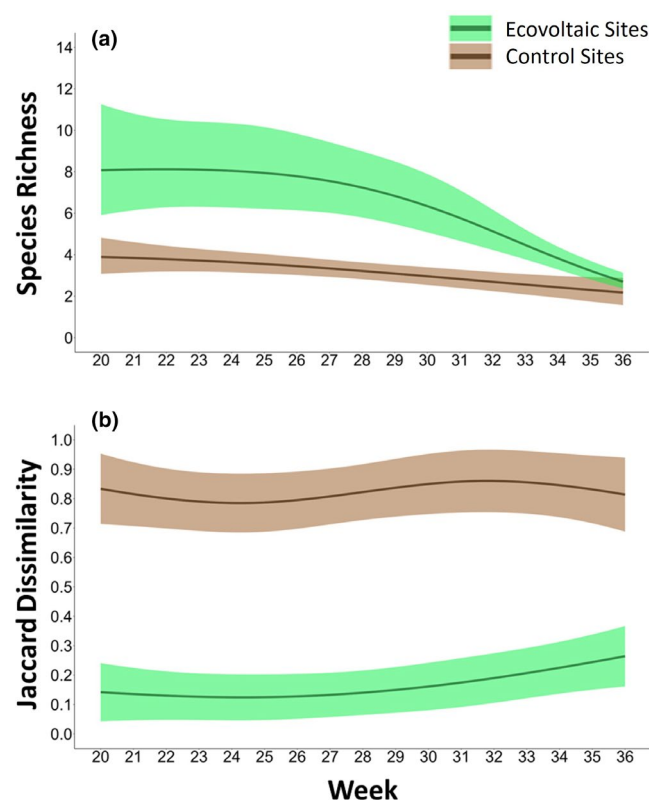


FIGURE 3 Predicted measures of (a) grassland bird species richness and (b) grassland bird community dissimilarity by week and location during the study period. Lines represent the predictions (with shaded 95% confidence intervals) using generalized additive models.

(Table 3). This model, which also included Ag500 as a covariate, explained approximately 62% of the variation in the data. Grassland bird species richness was consistently greater on the ecovoltic sites than in agricultural control sites throughout most of the season (Table 3; Figure 3a). The relative differences in species richness changed throughout the season, as evident by the significant interaction between week and ARU location (Table 3; Figure 3a). Early in the season (before Week 28), species richness was approximately two times greater on ecovoltic sites than on control sites. By the end of the season, grassland bird species richness was nearly equal at both locations.

3.3 | Community dissimilarity

Dissimilarity in the grassland bird communities, as measured by the Jaccard dissimilarity index, differed by ARU location (Table 3; Figure 3b). The best-performing model to predict dissimilarity included all suitable covariates (ARU location, Ag500, Habitat500, Tree500, Water500 and Latitude), explaining approximately 61% of the variation in the data. Throughout the 17-week monitoring season, there was consistently greater dissimilarity in the grassland bird communities at agricultural control fields than in ecovoltic sites (Figure 3b).

3.4 | Grassland bird occupancy

Naïve occupancy for grassland bird species across all 28 monitoring sites ranged from 0.07 (Swamp Sparrow [*Melospiza georgiana*]) to 0.86 (Red-winged Blackbird [*Agelaius phoeniceus*]), with an average of 0.57. Three of these species (Clay-coloured Sparrow [*Spizella pallida*], Sedge Wren [*Cistothorus stellaris*] and Swamp Sparrow) were detected at fewer than 10 sites and were omitted from occupancy modelling (Table 4). Occupancy models for the remaining species included location as a predictor for detection and occupancy parameters, and we further explored the additive effects of the other site and landscape covariates on occupancy probability. All selected occupancy models showed greater support than the null model, based on ΔAIC . However, selected models for two species did not greatly differ from their respective null models (e.g. $|\Delta AIC| \leq 2$ from the null model): Dickcissel and Horned Lark (*Eremophila alpestris*) (Table 4).

Overall, grassland birds had very similar detection probabilities (p) on solar sites and agricultural control fields (mean p for solar sites: 0.427; mean p for control sites: 0.417; Table S3). However, the influence of monitoring location on detection probability varied by species. Four species had significantly greater detection probabilities on solar sites than in agricultural controls: Dickcissel, Ring-necked Pheasant (*Phasianus colchicus*), Savannah Sparrow (*Passerculus sandwichensis*) and Vesper Sparrow (*Pooecetes gramineus*). Detection probabilities for two species were significantly greater in agricultural control fields than on solar sites: Chipping Sparrow (*Spizella passerina*) and Horned Lark (Table S3). In addition, there was a negative temporal effect on grassland bird detection probability (Table S3).

TABLE 4 Occupancy model results for grassland bird species. All models included ARU location and week as detection covariates.^a

Species	Number (and proportion) of solar sites with detections	Total sites (and proportion) with detections	Selected occupancy model	AIC (Δ AIC from null model)
Chipping Sparrow (<i>Spizella passerina</i>)	9 (0.56)	10 (0.36)	Location + Latitude	193.84 (–10.66)
Clay-coloured Sparrow (<i>Spizella pallida</i>)	8 (0.50)	9 (0.32)	NA—too few detections	
Dickcissel (<i>Spiza americana</i>)	16 (1.00)	23 (0.82)	Location	442.49 (–1.47)
Eastern Bluebird (<i>Sialia sialis</i>)	11 (0.68)	14 (0.50)	Location	266.40 (–3.53)
Eastern Kingbird (<i>Tyrannus tyrannus</i>)	13 (0.81)	22 (0.79)	Location + Tree500	436.90 (–3.41)
Eastern Meadowlark (<i>Sturnella magna</i>)	13 (0.81)	22 (0.79)	Location + Latitude	362.45 (–15.05)
Field Sparrow (<i>Spizella pusilla</i>)	13 (0.81)	17 (0.61)	Location + Latitude + Grass500	336.51 (–19.79)
Grasshopper Sparrow (<i>Ammodramus savannarum</i>)	7 (0.44)	15 (0.54)	Location + Latitude	308.29 (–13.45)
Horned Lark (<i>Eremophila alpestris</i>)	11 (0.68)	22 (0.79)	Location	385.69 (–0.24)
Northern Bobwhite (<i>Colinus virginianus</i>)	7 (0.44)	12 (0.43)	Location	253.25 (–3.99)
Red-winged Blackbird (<i>Agelaius phoeniceus</i>)	14 (0.87)	24 (0.86)	Location	393. (–3.74)
Ring-necked Pheasant (<i>Phasianus colchicus</i>)	9 (0.56)	15 (0.54)	Location + Latitude + Grass500	250.45 (–5.00)
Savannah Sparrow (<i>Passerculus sandwichensis</i>)	15 (0.94)	22 (0.79)	Location + Tree500	375.33 (–5.21)
Sedge Wren (<i>Cistothorus stellaris</i>)	2 (0.12)	4 (0.14)	NA—too few detections	
Swamp Sparrow (<i>Melospiza georgiana</i>)	2 (0.12)	2 (0.07)	NA—too few detections	
Vesper Sparrow (<i>Poocetes gramineus</i>)	13 (0.81)	19 (0.68)	Location + Tree500	310.89 (–4.78)

^aOccupancy models were developed for species detected at a minimum of 10 sites. The selected model was chosen from a suite of candidate models as the most parsimonious parameterized model within Δ AICc ≤ 2 from the model with the lowest AICc. See Tables S3-2 through S3-14 for complete model selection tables.

All species-specific occupancy models included week as a temporal observation-level detection covariate and ARU location as detection and occupancy covariates. Besides that, the selected models included up to two additional occupancy covariates (Table 4). Among the best-performing models, we were primarily interested in understanding the effect of ARU location on grassland bird occupancy. For this reason, we focused on the logit-scale parameter estimates ($\pm$ SE) for the effect of ARU location in each species-specific model. A positive parameter estimate indicated a greater occupancy probability on solar sites, and we considered this to be statistically influential if the standard error range did not include zero. Most grassland bird species showed greater modelled occupancy probabilities within solar sites than agricultural controls (Figure 4), but this effect was strongest for seven species: Chipping Sparrow (*Spizella passerina*), Vesper Sparrow (*Poocetes gramineus*), Ring-necked Pheasant, Field

Sparrow (*Spizella pusilla*), Dickcissel, Eastern Bluebird (*Sialia sialis*) and Savannah Sparrow. Only three grassland species had higher mean occurrence probabilities in agricultural control fields—Grasshopper Sparrow (*Ammodramus savannarum*), Horned Lark and Eastern Kingbird (*Tyrannus tyrannus*)—of which, only Grasshopper Sparrow and Horned Lark had logit-scale estimates that did not include zero (Figure 4).

4 | DISCUSSION

North American grassland bird populations have experienced a 53% decline since the 1970s (Rosenberg et al., 2019), due in large part to habitat loss and declines in insect prey populations (Samson & Knopf, 1994; Sánchez-Bayo & Wyckhuys, 2019). In theory, ecovoltaitic

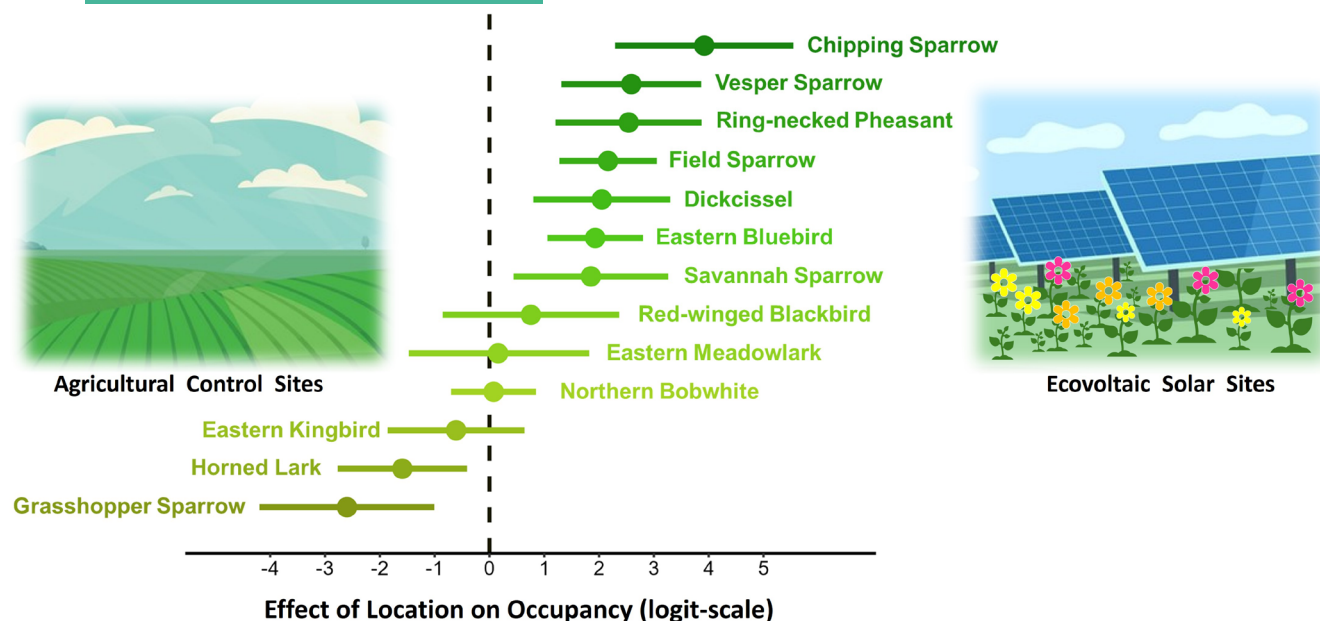


FIGURE 4 Effect of location (ecovoltaic site or control site) on occupancy for 13 grassland bird species. Values are based on parameter estimates from best-ranked occupancy models (based on AIC), using mean values for other covariates.

installations appropriately sited on previously disturbed lands have the potential to offset these trends by providing nesting, foraging and refuge habitat for bird populations. Our study is the first to empirically report on avian community responses to ecovoltaic sites in the U.S. Using PAM and BirdNET, we found that ecovoltaic sites supported greater grassland bird species richness than control sites throughout most of the study (Figure 3a).

Passive monitoring over several consecutive weeks allowed us to uncover temporal trends in the grassland bird communities utilizing ecovoltaic sites. We detected more grassland bird species on ecovoltaic sites throughout most of the 17-week monitoring season, but this difference narrowed as the season progressed (Figure 3a). This temporal pattern could be related to the seasonal occurrence of some species in the region, as evidenced by the decreasing weekly detection probabilities for all 13 modelled grassland species (Table S3). Most of these species are summer breeders in this region and were more frequently detected on solar sites before making fall migrations outside the region later in the season. By Week 36 (early September), proportionally more year-round resident bird species remained in the region, such as Northern Bobwhite (*Colinus virginianus*), Red-winged Blackbird and Ring-necked Pheasant (*Phasianus colchicus*).

Our analyses also revealed temporal differences in grassland bird β diversity between ecovoltaic sites and agricultural control fields. Weekly dissimilarity measures were consistently greater in control sites than in ecovoltaic sites (Figure 3b). Although all grassland species were detected on solar sites and agricultural controls, they were detected proportionately more on ecovoltaic solar sites than on agricultural controls (Table 4). The relatively infrequent detections in agricultural control fields created greater instability and contributed to increased

dissimilarity measures. Collectively, our species richness and β diversity analyses indicate that not only did ecovoltaic sites support more grassland bird species each week but also these communities were more stable than those in agricultural control fields. Community dissimilarity was largely a function of nestedness, as all species detected at agricultural control sites were subsets of species detected at ecovoltaic sites. These results are consistent with recent studies that have observed greater species richness and diversity at PV solar energy sites (Copping et al., 2025; Golawski et al., 2025; Jarčuška et al., 2024). For example, Jarčuška et al. (2024) found that PV solar sites in Slovakia (Central Europe) supported more bird species with greater β diversity than in control areas (grasslands).

This study demonstrated a PAM-based occupancy-modelling framework to quantify species-specific responses to solar energy development. This framework provides insight into which grassland bird species may be attracted to or avoid PV development in the Midwest (Figure 4). Ten out of the 13 modelled grassland species had greater predicted occupancy probabilities (ψ) on PV sites than control sites, with seven species showing the strongest preference for PV sites: Chipping Sparrow, Vesper Sparrow, Ring-necked Pheasant, Field Sparrow, Dickcissel, Eastern Bluebird and Savannah Sparrow. These findings suggest that most grassland bird species in the Midwest respond positively to solar energy facilities sited on lands formerly used for agriculture. Only two species, Grasshopper Sparrow and Horned Lark, exhibited stronger associations with agricultural controls (Figure 4). These species prefer open grasslands and are regularly observed in agricultural fields (Dinkins et al., 2022; Shaffer et al., 2021); thus, they may avoid the structural complexity of PV panels and associated solar energy infrastructure.

The conversion of row crop agriculture to ecovoltaic solar energy development represents a land use change that could have significant biodiversity implications across multiple trophic levels. Previous research has demonstrated the successful establishment of native grasses and forbs at ecovoltaic sites (McCall et al., 2024), which has resulted in the relatively rapid (e.g. <4 years) positive responses of insect communities that colonized the restored habitat at these sites (Blaydes et al., 2024; Walston et al., 2024). Higher trophic groups, such as birds and bats, may be attracted to these sites to forage on the increased abundance of insect prey or take advantage of nesting opportunities. A recent study found that bats in the Midwestern U.S. are attracted to ecovoltaic solar sites in spring and early summer months when insect abundance in surrounding farmland is low (Szoldatits et al., 2025). Consistent with these previous findings, our results show that native grassland bird communities, overall, are attracted to ecovoltaic solar facilities. Our findings also support several European studies that observed increased native bird species richness, abundance and diversity at PV sites in agricultural landscapes (Copping et al., 2025; Golawski et al., 2025; Jarčuška et al., 2024).

As a relatively new concept, there is no universal practical definition for the term 'ecovoltaic', given the global variability in factors such as PV siting, PV technology types, seed mix selection, vegetation management and associated ecological benchmarks to measure restoration performance. The frameworks established by Sturchio and Knapp (2023) and Tölgyesi et al. (2023) provide useful foundations to understand the role and function of ecovoltaic practices. These frameworks characterize ecovoltaic solar developments as PV developments situated on previously disturbed lands that co-prioritize electricity generation with the restoration of ecosystem function (e.g. habitat restoration). As such, a fundamental tenet of ecovoltaics is to create ecologically enhanced novel ecosystems that could result in a net positive effect on biodiversity (Tölgyesi et al., 2023).

While ecovoltaic designs show promise for biodiversity at large, species may respond differently to the unique vegetation assemblages, microclimates and structures (e.g. PV panels) created by these novel ecosystems, with some 'winner' species that are capable of successfully colonizing and exploiting these new environments, and some 'losers' that may avoid or be negatively affected by these installations (Filgueiras et al., 2021). Overall, the grassland bird community we evaluated showed positive responses to ecovoltaic developments in the Midwestern U.S. However, the avoidance of ecovoltaic sites by some species, such as Grasshopper Sparrow and Horned Lark, suggests that species that prefer open landscapes could 'lose' by the conversion of agricultural lands to ecovoltaic solar developments. These results are consistent with previous European studies which suggested that some species and taxonomic groups may not benefit from the conversion of agricultural lands to PV development (Bolonio et al., 2024; Kocsis et al., 2025). Our results are intended to provide initial insights into grassland bird species- and community-level responses to ecovoltaic developments in U.S. agricultural landscapes. Future work is needed to understand and mitigate the negative impacts that could occur to some species.

In general, birds may be attracted to ecovoltaic systems for refuge and as habitat for foraging and nesting. For example, proper vegetation management of these sites can improve the suitability of onsite vegetation for nesting (Copping et al., 2025; Golawski et al., 2025). Many species may be attracted to nest on or within the PV infrastructure, which may shelter nests from predators and extreme weather. Incidentally, we observed 236 active bird nests on or within the PV infrastructure across the 12 ecovoltaic solar sites during the course of this study. Most of these nests belonged to habitat generalists such as American Robin (*Turdus migratorius*), Barn Swallow (*Hirundo rustica*) and Mourning Dove (*Zenaidura macroura*), but we also detected nests of some grassland bird species (e.g. Dickcissel and Red-winged Blackbird). Other grassland bird species, such as Eastern Bluebird, have been documented to nest on PV infrastructure (Klehr et al., 2024). Birds may also be attracted to ecovoltaic systems to forage on the increased abundance of insect prey (Walston et al., 2024). While these factors can explain our results, future work should investigate whether increased avian occupancy at ecovoltaic solar sites results in improved fitness and population viability (e.g. nest success, collision mortality risk).

As a novel land management practice, additional work is needed to better understand the overall ecological value of ecovoltaic systems. This can be accomplished at a regional level by comparing biodiversity at these sites to those in degraded as well as undisturbed natural systems. Future research should also examine biodiversity responses across a range of ecovoltaic and non-ecovoltaic PV configurations in order to optimize the ecological effectiveness of ecovoltaic practices. The ecological effectiveness of ecovoltaic practices depends on a variety of factors including geographic region, solar facility siting and design and site-specific understanding of the ecological impacts of PV construction and operations. Therefore, ecovoltaic designs may not completely offset all negative ecological impacts resulting from PV developments sited in areas of high ecological value (e.g. native grassland systems). Instead, ecovoltaic systems have the greatest potential for ecological enhancement in areas that have been ecologically compromised (Tölgyesi et al., 2023; Walston et al., 2024), such as marginal farmland and other disturbed sites.

5 | CONCLUSIONS

Over 99% of the native prairie and grassland ecosystems of the Midwestern U.S. have been lost to human development and agricultural expansion since European settlement (Samson & Knopf, 1994). There is an opportunity to alleviate some of the ecological pressures resulting from this massively altered landscape by integrating habitat restoration and other ecological principles with appropriately sited renewable energy development. As of 2023, approximately 6.5 GW of large-scale ground-mounted PV installations were reported in the six-state region evaluated in this study (EIA, 2025), and a 2021 analysis showed that most of the PV developments in the region at

the time were constructed on former row crop agricultural fields (Walston et al., 2021). PV solar energy development is expected to continue in this region in the coming decades, and most of the region's future ground-mounted PV solar development is expected to occur on former row crop agricultural fields (Sorensen et al., 2022; Sturchio et al., 2025). Encouragingly, a growing number of PV developments in the U.S. are incorporating ecovoltaic principles. There are currently over 400 ecovoltaic sites in the U.S. (NREL, 2025), most of which are in the Midwest. If these PV siting trends continue, habitat-focused ecovoltaic solar designs in this region can offer a nature-based solution to reconcile human land uses with biodiversity conservation.

AUTHOR CONTRIBUTIONS

Leroy J. Walston, Heidi M. Hartmann, Laura Fox and Jordan Macknick designed the research. Leroy J. Walston, Heidi M. Hartmann, Laura Fox, Katherine E. Szoldatits, Melissa E. Stanger, Sophie E. Steele, Natalie R. Narváez and Irene Hogstrom conducted the fieldwork. Leroy J. Walston, Melissa E. Stanger, Sophie E. Steele and Natalie R. Narváez conducted data analyses. All authors participated in writing the paper.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

Data collected and analysed in this study are hosted and publicly available on Zenodo: <https://doi.org/10.5281/zenodo.17419964> (Walston, Hartmann, et al., 2025).

ETHICS STATEMENT

The article does not contain any studies involving human participants. There was no handling of birds or other organisms in this study.

STATEMENT ON INCLUSION

Our study spanned multiple U.S. states and included authors and student field work support (see Acknowledgments) from states where the study was carried out.

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REFERENCES

- Baselga, A. (2012). The relationship between species replacement, dissimilarity derived from nestedness, and nestedness. *Global Ecology and Biogeography*, 21, 1223–1232. <https://doi.org/10.1111/j.1466-8238.2011.00756.x>
- Bielski, L., Cansler, C. A., McGinn, K., Peery, M. Z., & Wood, C. M. (2024). Can the hermit warbler (*Setophaga occidentalis*) serve as an old-forest indicator species in the Sierra Nevada? *Journal of Field Ornithology*, 95(4), art4. <https://doi.org/10.5751/JFO-00390-950104>
- Blaydes, H., Potts, S. G., Whyatt, J. D., & Armstrong, A. (2024). On-site floral resources and surrounding landscape characteristics impact pollinator biodiversity at solar parks. *Ecological Solutions and Evidence*, 5, e12307. <https://doi.org/10.1002/2688-8319.12307>
- Bolonio, L., Moreno, E., La Calle, A., Montelío, E., & Valera, F. (2024). Renewable energy acceleration endangers a protected species: Better stop to light a torch than run in the dark. *Environmental Impact Assessment Review*, 105, 107432. <https://doi.org/10.1016/j.eiar.2024.107432>
- Burnham, K. P., & Anderson, D. R. (2002). *Model selection and multi-model inference: A practical information-theoretic approach* (2nd ed.). Springer.
- Copping, J. P., Waite, C. E., Balmford, A., Bradbury, R. B., Field, R. H., Morris, I., & Finch, T. (2025). Solar farm management influences

- breeding bird responses in an arable-dominated landscape. *Bird Study*, 72, 217–222. <https://doi.org/10.1080/00063657.2025.2450392>
- Darras, K., Batáry, P., Furnas, B., Celis-Murillo, A., Van Wilgenburg, S. L., Mulyani, Y. A., & Tschardtke, T. (2018). Comparing the sampling performance of sound recorders versus point counts in bird surveys: A meta-analysis. *Journal of Applied Ecology*, 55, 2575–2586. <https://doi.org/10.1111/1365-2664.13229>
- Dinkins, M. F., Igl, L. D., Shaffer, J. A., Johnson, D. H., Zimmerman, A. L., Parkin, B. D., Goldade, C. M., & Euliss, B. R. (2022). *The effects of management practices on grassland birds—Horned Lark (Eremophila alpestris)*. U.S. Geological Survey Professional Paper 1842-U. <https://doi.org/10.3133/pp1842U>
- Filgueiras, B. K., Peres, C. A., Melo, F. P., Leal, I. R., & Tabarelli, M. (2021). Winner–loser species replacements in human-modified landscapes. *Trends in Ecology & Evolution*, 36, 545–555. <https://doi.org/10.1016/j.tree.2021.02.006>
- Fiske, I., & Chandler, R. (2011). Unmarked: An R package for fitting hierarchical models of wildlife occurrence and abundance. *Journal of Statistical Software*, 43(10), 1–23.
- Golawski, A., Mitrus, C., & Jankowiak, L. (2025). Increased bird diversity around small-scale solar energy plants in agricultural landscape. *Agriculture, Ecosystems & Environment*, 379, 109361. <https://doi.org/10.1016/j.agee.2024.109361>
- Goldberg, Z. A. (2023). Solar energy development on farmland: Three prevalent perspectives of conflict, synergy and compromise in the United States. *Energy Research & Social Science*, 101, 103145. <https://doi.org/10.1016/j.erss.2023.103145>
- Gómez-Catasús, J., Morales, M. B., Giralt, D., González del Portillo, D., Manzano-Rubio, R., Solé-Bujalance, L., Sardà-Palomera, F., Traba, J., & Bota, G. (2024). Solar photovoltaic energy development and biodiversity conservation: Current knowledge and research gaps. *Conservation Letters*, 17, e13025. <https://doi.org/10.1111/conl.13025>
- Hack, B., Cansler, C. A., Peery, M. Z., & Wood, C. M. (2024). Fine-scale forest structure, not management regime, drives occupancy of a declining songbird, the olive-sided flycatcher, in the core of its range. *Ornithological Applications*, 126, duad065. <https://doi.org/10.1093/ornithapp/duad065>
- Heit, D. R., Ortiz-Calo, W., Poisson, M. K. P., Butler, A. R., & Moll, R. J. (2024). Generalized nonlinearity in animal ecology: Research, review, and recommendations. *Ecology and Evolution*, 14, e11387. <https://doi.org/10.1002/ece3.11387>
- International Energy Agency [IEA]. (2024). *Renewables 2024—Analysis and forecast to 2030*. <https://www.iea.org/reports/renewables-2024>
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning: With applications in R*. Springer. <https://doi.org/10.1007/978-1-4614-7138-7>
- Jarčuška, B., Gálffyová, M., Schnürmacher, R., Baláž, M., Mišík, M., Repel, M., Fulín, M., Kerestúr, D., Lackovičová, Z., Mojžiš, M., Zámečník, M., Kaňuch, P., & Krištín, A. (2024). Solar parks can enhance bird diversity in agricultural landscape. *Journal of Environmental Management*, 351, 119902. <https://doi.org/10.1016/j.jenvman.2023.119902>
- Johnson, D. H., Igl, L. D., Shaffer, J. A., & DeLong, J. P. (2019). *The effects of management practices on grassland birds*. U.S. Geological Survey Professional Paper 1842. <https://doi.org/10.3133/pp1842>
- Kahl, S., Wood, C. M., Eibl, M., & Klinck, H. (2021). BirdNET: A deep learning solution for avian diversity monitoring. *Ecological Informatics*, 61, 101236. <https://doi.org/10.1016/j.ecoinf.2021.101236>
- Karban, C. C., Lovich, J. E., Grodsky, S. M., & Munson, S. M. (2024). Predicting the effects of solar energy development on plants and wildlife in the Desert Southwest, United States. *Renewable and Sustainable Energy Reviews*, 205, 114823. <https://doi.org/10.1016/j.rser.2024.114823>
- Klehr, A. L., Laskowski, A. N., & King, D. I. (2024). Eastern bluebirds (*Sialia sialis*) nesting in photovoltaic solar energy facilities in eastern New York. *Northeastern Naturalist*, 31, N30–N34. <https://doi.org/10.1656/045.031.0405>
- Kocsis, T., de Groot, A., van Beersum, F., Boer, J., Dimmers, W., Laros, I., Lammertsma, D., Polling, M., Schnerch, B., Villing, N., & WallisDeVries, M. F. (2025). Mixed plant and arthropod biodiversity responses to solar park establishment on former agricultural lands. *Journal of Applied Ecology*, 62, 3078–3091. <https://doi.org/10.1111/1365-2664.70170>
- Kosciuch, K., Riser-Espinoza, D., Moqtaderi, C., & Erickson, W. (2021). Aquatic habitat bird occurrences at photovoltaic solar energy development in southern California, USA. *Diversity*, 13, 524. <https://doi.org/10.3390/d13110524>
- Kosicki, J. Z. (2020). Generalized additive models and random forest approach as effective methods for predictive species density and functional species richness. *Environmental and Ecological Statistics*, 27, 273–292. <https://doi.org/10.1007/s10651-020-00445-5>
- MacDonald, G. J., Anteau, M. J., Ellis, K. S., Igl, L. D., Niemuth, N. D., & Vest, J. L. (2024). *Seasonal breeding phenologies of 38 grassland bird species in the midcontinent of North America*. U.S. Geological Survey Open-File Report 2024–1002. <https://doi.org/10.3133/ofr20241002>
- McCall, J. B., Beatty, J., Janski, K., Doubleday, J., Martin, H., Hartmann, L. J., Walston, L., & Macknick, J. (2024). Little prairie under the panel: Testing native pollinator habitat seed mix establishment at three utility-scale solar sites in Minnesota. *Environmental Research Communications*, 6, 075012. <https://doi.org/10.1088/2515-7620/ad5b3c>
- National Renewable Energy Laboratory [NREL]. (2025). *Agrivoltaics map*. https://openei.org/wiki/InSPIRE/Agrivoltaics_Map
- Nijse, F. J. M. M., Mercure, J.-F., Ameli, N., Larosa, F., Kothari, S., Rickman, J., Vercoolen, P., & Pollitt, H. (2023). The momentum of the solar energy transition. *Nature Communications*, 14, 6542. <https://doi.org/10.1038/s41467-023-41971-7>
- Pedersen, E. J., Miller, D. L., Simpson, G. L., & Ross, N. (2019). Hierarchical generalized additive models in ecology: An introduction with mgcv. *PeerJ*, 7, e6876. <https://doi.org/10.7717/peerj.6876>
- R Core Team. (2024). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing.
- Rosenberg, K. V., Dokter, A. M., Blancher, P. J., Sauer, J. R., Smith, A. C., Smith, P. A., Stanton, J. C., Panjabi, A., Helft, L., Parr, M., & Marra, P. P. (2019). Decline of the north American avifauna. *Science*, 366, 120–124. <https://doi.org/10.1126/science.aaw1313>
- Samson, F., & Knopf, F. (1994). Prairie conservation in North America. *BioScience*, 44, 418–421. <https://doi.org/10.2307/1312365>
- Sánchez-Bayo, F., & Wyckhuys, K. A. (2019). Worldwide decline of the entomofauna: A review of its drivers. *Biological Conservation*, 232, 8–27. <https://doi.org/10.1016/j.biocon.2019.01.020>
- Schuster, G., Walston, L. J., & Little, A. R. (2024). Evaluation of an autonomous acoustic surveying technique for grassland bird communities in Nebraska. *PLoS One*, 19, e0306580. <https://doi.org/10.1371/journal.pone.0306580>
- Shaffer, J. A., Igl, L. D., Johnson, D. H., Sondreal, M. L., Goldade, C. M., Nenneman, M. P., Wooten, T. L., & Euliss, B. R. (2021). *The effects of management practices on grassland birds—Grasshopper Sparrow (Ammodramus savannarum)*. U.S. Geological Survey Professional Paper 1842. <https://doi.org/10.3133/pp1842GG>
- Sorensen, A., Nogeire, T., & Hunter, M. (2022). *Potential placement of utility-scale solar installations on agricultural lands in the U.S. to 2040*. American Farmland Trust. https://farmlandinfo.org/wp-content/uploads/sites/2/2023/03/AFT_FUT2040-solar-white-paper.pdf
- Sturchio, M. A., Gallaher, A., & Grodsky, S. M. (2025). Ecologically informed solar enables a sustainable energy transition in U.S. croplands. *Proceedings of the National Academy of Sciences of the United States of America*, 122, e2408111122. <https://doi.org/10.1073/pnas.2408111122>

- States of America, 122, e2501605122. <https://doi.org/10.1073/pnas.2501605122>
- Sturchio, M. A., Kannenberg, S. A., & Knapp, A. K. (2024). Agrivoltaic arrays can maintain semi-arid grassland productivity and extend the seasonality of forage quality. *Applied Energy*, 15, 122418. <https://doi.org/10.1016/j.apenergy.2023.122418>
- Sturchio, M. A., & Knapp, A. K. (2023). Ecovoltaic principles for a more sustainable, ecologically informed solar energy future. *Nature Ecology & Evolution*, 7, 1746–1749. <https://doi.org/10.1038/s41559-023-02174-x>
- Sugai, L. S. M., Silva, T. S. F., Ribeiro, J. W., Jr., & Llusia, D. (2019). Terrestrial passive acoustic monitoring: Review and perspectives. *BioScience*, 69, 15–25. <https://doi.org/10.1093/biosci/biy147>
- Szoldatits, K. E., Walston, L. J., Hartmann, H. M., Fox, L., Stanger, M. E., Steele, S. E., Hogstrom, I., & Macknick, J. (2025). Bat activity at ecovoltaic solar energy developments in the midwestern United States. *Global Ecology and Conservation*, 63, e03864. <https://doi.org/10.1016/j.gecco.2025.e03864>
- Tölgyesi, C., Batori, Z., Pascarella, J., Erdős, L., Török, P., Batáry, P., Birkhofer, K., Scherer, L., Michalko, R., Košulič, O., Zaller, J. G., & Gallé, R. (2023). Ecovoltics: Framework and future research directions to reconcile land-based solar power development with ecosystem conservation. *Biological Conservation*, 285, 110242. <https://doi.org/10.1016/j.biocon.2023.110242>
- Treasure, L., Harrison, L. J., Hudson, P., You, J., Hawkins, D., Grier, R., Lee, H. K., Armstrong, A., & White, P. C. L. (2024). *Nature Positive solar investment: industry guidance*. https://eprints.whiterose.ac.uk/215482/14/NPSI_report_2024.pdf
- U.S. Department of Energy [DOE]. (2021). *Solar futures study*. Department of Energy, Office of Energy Efficiency and Renewable Energy. <https://www.energy.gov/eere/solar/solar-futures-study>
- U.S. Energy Information Administration [EIA]. (2025). *Electricity—Form EIA-860 detailed data*. <https://www.eia.gov/electricity/data/eia860/>
- Walston, L. J., Cacho, J. F., Lesmes-Vesga, R. A., Sandhu, H., Zumpf, C. R., Kasberg, B., Feinstein, J., & Negri, M. C. (2025). *Passive acoustic monitoring provides insights into avian use of energycane cropping systems in southern Florida*. <https://doi.org/10.20944/preprints202506.2152.v1>
- Walston, L. J., Hartmann, H. M., Fox, L., Macknick, J., McCall, J., Janski, J., & Jenkins, L. (2024). If you build it, will they come? Insect community responses to habitat establishment at solar energy facilities in Minnesota, USA. *Environmental Research Letters*, 19, 014053. <https://doi.org/10.1088/1748-9326/ad0f72>
- Walston, L. J., Hartmann, H. M., Fox, L., Stanger, M. E., Steele, S. E., Narváez, N. R., Szoldatits, K. E., Hogstrom, I., & Macknick, J. (2025). Data from: Ecovoltaic solar energy development can promote grassland bird communities. *Zenodo Digital Repository*, <https://doi.org/10.5281/zenodo.17419964>
- Walston, L. J., Li, Y., Hartmann, H. M., Macknick, J., Hanson, A., Nootenboom, C., Lonsdorf, E., & Hellmann, J. (2021). Modeling the ecosystem services of native vegetation management practices at solar energy facilities in the midwestern United States. *Ecosystem Services*, 47, 101227. <https://doi.org/10.1016/j.ecoser.2020.101227>
- Wehbi, H. (2024). Powering the future: An integrated framework for clean renewable energy transition. *Sustainability*, 16, 5594. <https://doi.org/10.3390/su16135594>
- Wood, C., Sullivan, B., Iliff, M., Fink, D., & Kelling, S. (2011). eBird: Engaging birders in science and conservation. *PLoS Biology*, 9, e1001220. <https://doi.org/10.1371/journal.pbio.1001220>
- Wood, C. M., & Kahl, S. (2024). Guidelines for appropriate use of BirdNET scores and other detector outputs. *Journal of Ornithology*, 165, 777–782. <https://doi.org/10.1007/s10336-024-02144-5>
- Wood, C. M., Socolar, J., Kahl, S., Peery, M. Z., Chaon, P., Kelly, K., Koch, R. A., Sawyer, S. C., & Klinck, H. (2024). A scalable and transferable approach to combining emerging conservation technologies to identify biodiversity change after large disturbances. *Journal of Applied Ecology*, 61, 797–808. <https://doi.org/10.1111/1365-2664.14579>

SUPPORTING INFORMATION

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

Data S1. BirdNET results.

Data S2. Generalized additive models.

Data S3. Grassland bird occupancy models.

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