

CONTRIBUTED PAPER

Climate policy action needed to reduce vulnerability of conservation-reliant grassland birds in North America

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Funding information

John D. and Catherine T. MacArthur Foundation, Grant/Award Number: G-1511-150388; Natural Resources Conservation Service, Grant/Award Number: 69-3A75-17-320

Grassland birds have suffered dramatic population declines and are under threat of further grassland conversion. Simultaneously, grassland regions are projected to have high rates of future climate change. We assessed the vulnerability of grassland birds in North America under scenarios of global climate change reflecting the objectives of the Paris Agreement. The assessment incorporated model-based projections of range losses and gains as well as trait-based information on adaptive capacity. Nearly half (42%) of grassland birds were highly vulnerable during the breeding season under a 3.0°C increase in global mean temperature scenario representing current commitments under the Paris Accord. This proportion declined to 13% with a 2.0°C increase and to 8% with a 1.5°C increase over preindustrial global mean temperature. Regardless of scenario, more than 70% of grassland birds had some vulnerability to climate change. Policy actions beyond the present-day national commitments under the Paris Accord are needed to reduce vulnerability of grassland birds in a changing climate.

KEYWORDS

citizen science, climate change vulnerability, global change, Paris Accord, species distribution model

1 | INTRODUCTION

Temperate grasslands are at risk globally due to extensive land conversion and comparatively little land conservation in spite of their high conservation value (Hoekstra, Boucher, Ricketts, & Roberts, 2005). The northern and tallgrass prairies of North America, in particular, have high irreplaceability (Brooks et al., 2006) and were identified as critically endangered among the Global 200 priority ecoregions for conservation (Olson & Dinerstein, 2002). Yet, net land conversion rates were locally as high as 10% from 2008 to 2012 in some regions of the United States, with 77% of new cropland coming from grasslands (Lark, Salmon, & Gibbs, 2015).

Extensive habitat loss in North American grasslands has resulted in wildlife population declines. Since the 1970s, habitat loss from conversion to row-crops, along with interference from farming activities and exposure to pesticides has directly impacted bird abundance, survival, and reproduction (Stanton, Morrissey, & Clark, 2018). Observed declines in U.S. grassland bird populations are >40% since 1966 (North American Bird Conservation Initiative [NABCI], 2017). Remaining grasslands are highly fragmented and limited in their capacity to support diverse bird communities, including the most vulnerable species which require large, contiguous grasslands (e.g., >260 ha, Johnson, Granfors, Niemuth, Estey, & Reynolds, 2010). As a result, 27% of North American

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grassland bird species are considered of high conservation concern (NABCI, 2016).

Climate change may further threaten grasslands and grassland birds. Temperate grassland regions are projected to have some of the highest climate change velocities (a measure of the speed of travel needed to keep pace with climate change) among biomes on Earth (Loarie et al., 2009). Over the last 60 years bird species within grassland ecosystems have experienced bioclimatic velocities at a rate of 1.3 km/year, more than double the pace of distribution shift estimates across terrestrial systems globally (0.61 km/year) (Bateman et al., 2016). Furthermore, the limited availability and fragmentation of grassland habitat may complicate grassland birds' ability to track warming, making these species even more vulnerable to climate change (McGuire, Lawler, McRae, Nuñez, & Theobald, 2016).

Shifts in wildlife distributions are a recognized fingerprint of climate change (Parmesan & Yohe, 2003). Globally, studies examining responses to climate change across taxa found significant impacts on population parameters, with a negative response to rising temperatures and positive response to precipitation (Pearce-Higgins et al., 2015). Projections of avian distribution shifts in response to climate change correlated with observed changes in abundance in both Europe and North America (Stephens et al., 2016). In the United States, birds have demonstrated multidirectional shifts rather than a uniform response to warming with both changes in temperature and more extreme weather events contributing (Bateman et al., 2016). Clearly, climate responses are species-specific, and sensitive relative to other drivers such as trophic interactions and land-use change (Rapacciuolo et al., 2014).

In spite of the potential risk, few national policies reduce the threat of climate change sufficiently. The Paris Agreement (United Nations [UN], 2015) includes 174 ratified parties (mostly nations) committed to reducing greenhouse gas emissions or increasing carbon sequestration. The agreement aims to limit global mean temperature increases to less than 2°C above preindustrial levels; a level of warming above which the risks of climate change to human civilization and the natural world are greatly increased (IPCC, 2013). Here, we assess the risk of climate change to grassland birds using a model-based Climate Change Vulnerability Assessment (CCVA) for 38 species of North American grassland birds across Canada, the United States, and Mexico. We used projections of climate suitability for the breeding and nonbreeding seasons along with trait-based information on dispersal to generate a novel index of climate change vulnerability. We generated vulnerability scores for three policy-relevant scenarios: 1.5, 2.0, and 3°C increases in global mean temperature. The objective of this study was to assess how climate change vulnerability for grassland

birds in North America changed under three scenarios reflecting current and potential climate change targets.

2 | METHODS

The Intergovernmental Panel on Climate Change (IPCC) suggests estimating vulnerability to climate change as a function of a species' exposure to change, its sensitivity to those changes, and its adaptive capacity in the face of change (Foden & Young, 2016). In practice, CCVAs use a range of approaches (Foden & Young, 2016; Pacifici et al., 2015; Willis et al., 2015). Correlative approaches make use of future projections from species distribution models (i.e., niche models; Peterson et al., 2011) to assess vulnerability. Mechanistic assessments simulate biological responses to climate (e.g., demography, Bancroft, Lawler, & Schumaker, 2016 or dispersal, Morin & Thuiller, 2009). Trait-based approaches make use of published literature and expert opinion to score species based on their biological traits (Foden et al., 2013). And, combined (i.e., hybrid) approaches take elements of one approach and integrate them into another, such as using natal dispersal and generation times to restrict projections of species distribution models by a biologically meaningful maximum dispersal distance for the projection period (Willis et al., 2015). Combined approaches, when available data allows, are desirable because they address the limitations of any one approach (Willis et al., 2015). We conducted a CCVA for 38 species of North American grassland birds across Canada, United States, and Mexico using a combination of correlative models and trait-based information.

2.1 | Avian and environmental data

In order to build ecological niche models for 38 grassland birds we assembled bird observation data and covariates of climate and habitat for the portion of North America spanning Mexico, the United States, and Canada. We compiled bird occurrences from >40 datasets (see Supporting Information for more details) to create the largest known database of presence records for grassland birds (~4.1 million records). Records with incomplete geographic coordinates were removed, along with records including metadata identifying surveys covering lengthy distances (>1 km), large areas (>100 ha), long durations (>180 min), and those occurring outside of daylight hours (5 a.m.–8 p.m.). We also filtered by date ranges to build breeding (June–July), resident (year-round), and nonbreeding (December–January) models. We included 36 native terrestrial grassland species based on NABCI's 2009 State of the Birds habitat classifications, as well as 2 introduced grassland game-species (Gray Partridge [*Perdix perdix*] and Ring-necked Pheasant [*Phasianus colchicus*]). Some were not grassland-obligate species, and environmental covariates

included other landcover types to distinguish selected and avoided landcover. We reviewed published range maps to determine if a species had a separate breeding and nonbreeding range. For the four species whose nonbreeding range was mostly outside of the study area, we modeled only the breeding season.

We used current and modeled future climate developed by AdaptWest (Wang, Hamann, Spittlehouse, & Carroll, 2016) as climate covariates in our models. Climate grids consisted of 23 million grid cells covering the study area at a 1 km resolution. We used statistically downscaled climate normals from 1981 to 2010 derived from the Climatic Research Unit Timeseries 3.22 dataset (crudata.uea.ac.uk/cru/data/hrg/) to represent current climate for model parameterization and validation (Wang et al., 2016). We used climate projections based on the Coupled Model Intercomparison Project phase 5 (CMIP5) from three individual General Circulation Models (GCMs) (CCSM4, GFDL-CM3, and INM-CM4) and an ensemble of 15 GCMs under two greenhouse gas concentration trajectories (RCPs 4.5 and 8.5) for two future time periods (2050s and 2080s) to represent future conditions and to assess vulnerability. We associated projections to the 2050s under RCP 4.5 with the 1.5°C global mean temperature rise policy scenario, and projections under RCP 8.5 to the 2050s and 2080s with the 2.0°C and 3.0°C policy scenarios, respectively. Here, we report results based on the 15-GCM ensemble projection. This is an average projection; therefore, we also assessed agreement in our vulnerability classifications by comparing ensemble projections with three individual GCMs that capture the range of warm-wet (GFDL-CM3) and cold-dry (INM-CM4) and intermediate (CCSM4) futures projected for the continent (Wang et al., 2016).

We built breeding season models (including residents and migrants) for 38 species and nonbreeding season models for 34 species (including residents and migrants). Each species model included either 10 (breeding) or 11 (nonbreeding) environmental covariates (Table 1). These were selected from a set of 27 variables (see Supporting Information Appendix 1 for a complete list grouped using hierarchical agglomerative clustering of 100,000 points randomly placed across the study area, Crowther et al., 2015). All models included the annual climatic covariates of climatic moisture deficit (CMD), number of frost-free days, mean annual precipitation (MAP), and precipitation as snow (PAS); and non-climatic covariates for land-use, vegetation, and terrain ruggedness. Summer models also included seasonal climate covariates (mean temperature of the warmest month, degree-days below 0°C [chilling degree days], and summer heat moisture index), as did winter models (mean temperature of the coldest month, degree-days above 5°C [growing degree days]). Land-use was represented by a static categorical map of only anthropogenic land-use classes (e.g., agriculture and developed) derived from the Commission for Environmental

TABLE 1 Variables included as predictors in the species distribution models

Type	Variable	Season
Climate	Hargreave's climatic moisture index	Breeding and nonbreeding
Climate	Degree-days below 0°C (chilling degree days)	Breeding
Climate	Degree-days above 5°C (growing degree days)	Nonbreeding
Climate	Mean annual precipitation (mm)	Breeding and nonbreeding
Climate	Mean temperature of the coldest month (°C)	Nonbreeding
Climate	Mean temperature of the warmest month (°C)	Breeding
Climate	Number of frost-free days	Breeding and nonbreeding
Climate	Precipitation as snow (mm)	Breeding and nonbreeding
Climate	Summer heat moisture index	Breeding
Environment	Topographic roughness index	Breeding and nonbreeding
Environment	Anthropogenic land use	Breeding and nonbreeding
Environment	Vegetation type	Breeding and nonbreeding

Cooperation's (CEC) North American Environmental Atlas 2010 landcover dataset (Canada Centre for Remote Sensing et al., 2013). Present and future vegetation was extracted from modeled distributions of 46 North American biomes (Rehfeldt, Crookston, Sáenz-Romero, & Campbell, 2012). Much like what was done for climate covariates (described above), mid-century (2050s) vegetation projections were used in the 1.5 and 2.0°C global mean temperature rise policy scenarios, and late-century (2090s) projections were used for the 3.0°C global mean temperature rise scenario. Vegetation projections were the consensus projection across three CMIP3 GCMs (CGCM3, HadCM3, GFDL CM2.1) model projections run under two SRES emissions scenarios (A2 and B1 or B2). Thus, neither the GCMs nor the emissions scenarios for vegetation aligned directly with those for climate covariates. We included these consensus-based projections of vegetation distribution because they are the best available projections at a continental scale, and because the CMIP3 and CMIP5 projections are more similar than distinct (Knutti & Sedláček, 2013). We derived terrain ruggedness from a digital elevation model (Riley, DeGloria, & Elliot, 1999). See Appendix 1 in Supporting Information for further details on their preparation.

2.2 | Species distribution modeling

Recent work in the field of species distribution modeling has identified a number of data preparation approaches that improve model performance and transferability (Boria, Olson, Goodman, & Anderson, 2014; Peterson et al., 2011; Radosavljevic & Anderson, 2014). These approaches

incorporate species-specific biological information into the model-construction process, address issues of underlying sampling bias in the datasets used (Yackulic et al., 2013), and improve model generalizability by minimizing overfitting (Veloz, 2009). Here, we applied some of the latest approaches in a species-focused modeling process with the goal of producing the best occurrence model for each species, in contrast to one-size-fits-all approaches (e.g., Lawler et al., 2009).

The modeling process involved data extraction, partitioning, and filtering; model construction and evaluation; and prediction (Figure 1, see Supporting Information Appendix 1 for detailed methods). We applied techniques for presence-only modeling (Radosavljevic & Anderson, 2014). Our combined dataset of both structured and unstructured monitoring data includes inherent sampling bias due to volunteer participation and nonrandom survey locations (Phillips et al., 2009; Yackulic et al., 2013) which we addressed in four ways. First, we used target-group background sampling (Phillips et al., 2009) weighted by the number of checklists recorded in each grid cell. Second, we selected background observations from regions occupied by the species plus a buffer region that a species could have historically experienced through movement (Peterson et al., 2011). To do this for each species and season, we identified the Bird Conservation Regions (BCRs, NABCI, <http://nabci.us.org/resources/bird-conservation-regions-map/>) into which these presence observations fell and selected background data from only those and adjacent BCRs. We assumed that

BCRs captured relevant biological barriers to movement and that species had experienced adjacent BCRs historically. This movement-hypothesis approach improves model prediction performance and the generalizability of the species-environment relationships modeled therein (Boria et al., 2014). Third, we used a masked geographically structured approach towards data partitioning (Radosavljevic & Anderson, 2014) for rigorous model assessment. Nonrandom spatial structure was added by overlaying a 200-km grid over the study area and randomly assigning observations from those areas to training and test datasets (Wenger & Olden, 2012). A 200-km grid was selected after examining the ranges of semivariograms produced for each environmental variable and determining that variation leveled off above 200-km. In each bootstrapped dataset, observations from grid cells assigned to training represented 25% of observations in that dataset. This modified grid-sampling algorithm also maintained a constant prevalence between the training and evaluation datasets (as in Wilsey, Jensen, & Miller, 2016). Finally, we filtered observations using both geographic (Boria et al., 2014) and environmental (Varela, Anderson, García-Valdés, & Fernández-González, 2014) approaches to reduce bias and minimize model overfitting. We tested multiple geographic resolutions (1, 10, and 50-km) and numbers of environmental bins (5, 25, 50) for filtering. We built occurrence models with both boosted regression trees (Elith & Leathwick, 2014) and Maxent (Phillips & Dudík, 2008) with the R package *dismo* (Hijmans, Phillips, Leathwick, & Elith, 2015), evaluated

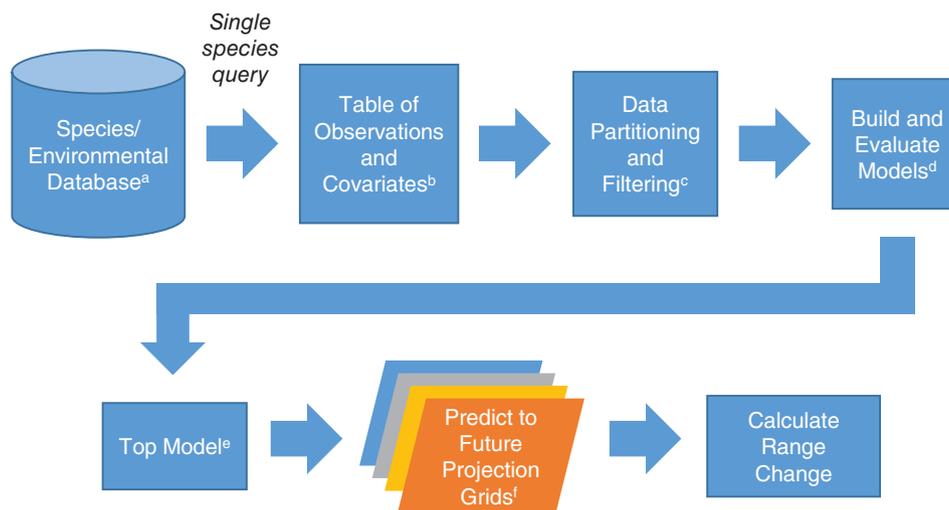


FIGURE 1 Flowchart for model-based estimates of range stability, gain, and loss used to estimate climate change exposure and sensitivity. See Appendix 1 in the supporting information for detailed methods. (a) Multitable database mapped all observations and environmental data to a common, 1-km grid of North America. Tables include presences records, sampling locations, environmental covariates, and climate covariates. (b) Observations and covariate table included only points that fall within the Bird Conservation Regions (BCR) in which the species was observed and any adjacent BCRs. We excluded other areas of the continent from the analysis. (c) Data were partitioned 25 times into unique spatially stratified (200-km resolution) training and test datasets. We filtered training data using both geographic and environmental filtering procedures at three resolutions. Test datasets remained unfiltered. The same set of 25 training and test datasets for each species were used across data filtering approaches to allow direct performance comparisons. (d) Boosted regression tree models were built for each filtering approach and resolution. We built Maxent models for only the best performing geographic and environmental filtering approach. We based our model evaluation on median AUC across all 25 spatially stratified test datasets. (e) A top-performing model (Maxent or boosted regression tree and top-performing filtering approach and resolution) was selected for each species. (f) Predictions were based on three GCMs (CCSM4, GFDL-CM3, and INM-CM4) plus 15-GCM ensemble run under two RCP scenarios (4.5 and 8.5) and for two future time periods (2055, 2085)

based on median area under the receiver-operator curve (AUC) across the spatially stratified 25 bootstrapped datasets, and selected a top model per species looking across observation filtering approaches, resolutions, and modeling algorithms (i.e., boosted regression trees vs. Maxent). The 25 bootstrapped training and test datasets were the same for all models generated for a given species, allowing for direct comparisons of performance. In total, we built 525 models for each species for model evaluation testing these assorted techniques for improving model performance and removing bias (see Appendix 1 in Supporting Information for further details).

We generated high-resolution (1-km) predictive occurrence maps for each time period, greenhouse gas concentration trajectory, and GCM. We limited extrapolation by not projecting to vegetation or land-use classes not included in the model training datasets. Similarly, we masked from all current and future climate projections geographically distinct BCRs for which the modeled current distribution demonstrated commission error (i.e., over-prediction). These were primarily BCRs in the Arctic and Mexico and this masking was done for 13 species in summer and 7 in winter. We converted projected future suitability into presence/absence maps by applying a suitability threshold based on the true skill statistic (Allouche, Tsoar, & Kadmon, 2006) for most species. However, for three species an alternative suitability threshold (minimum omission of 10% [*Spizella pallida*] or mean prediction value [*Rhynchophanes mccownii* & *Ammodramus nelsoni*]) was selected for which the present day projection aligned more closely with expert opinion with minimal decline in model performance (Reside et al., 2019). For breeding and resident models, we used estimates of mean natal dispersal (BirdLife International, 2017) and generation time (Beauchamp, 2009) to generate an estimated

dispersal limit for each future time period. We assumed a generation time of 1 year when it was unknown (e.g., *Peucaea botterii* and *Bartramia longicauda*). We used these limits to clip maps of future climate suitability such that projected distributions reflected biological limits to dispersal. Information on nonbreeding site fidelity and movement is often unknown, so we made no modifications to projected nonbreeding season distributions.

2.3 | Climate change vulnerability assessment

We assessed vulnerability for each of three climate change exposure scenarios (1.5, 2.0, and 3.0°C increase in global mean temperature) from projected range loss and potential expansion (as in Langham, Schuetz, Distler, Soykan, & Wilsey, 2015; Thomas et al., 2010). To characterize climate sensitivity, we used range loss (the proportion of the current range projected to be unsuitable in the future), and assigned scores from 0 to 3 in increasing order to range losses of 0–25, 25–50, 50–75, and 75–100% (Figure 2). We assessed adaptive capacity by the ratio of projected range gain to loss. Limiting future projections by dispersal potential incorporated an additional element of adaptive capacity beyond measures of niche breadth and habitat associations captured in the species' models themselves. We considered species projected to experience overall range loss to have low adaptive capacity and species with overall range gain to have high adaptive capacity. We then assigned scores between 0 and 3 in decreasing order when the ratio of projected range gain to loss was >2:1, 1–2:1, 0.5–1:1, and 0–0.5:1, and then added the two scores for a final vulnerability score (Figure 2). A species has nonneutral vulnerability if it loses 25% or more of its current range, or does not have potential to gain back twice the amount of range that is lost.

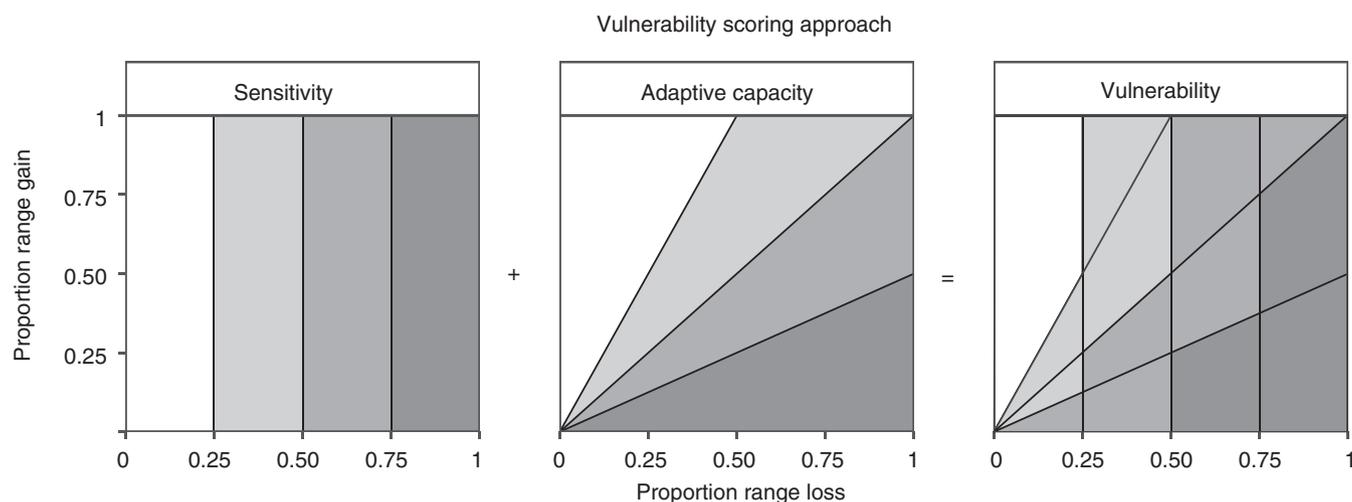


FIGURE 2 Vulnerability assessments based on model-based estimates of climate exposure and hybrid model-based and trait-based estimates of combined sensitivity and adaptive capacity. Darker colors correspond to higher vulnerability. We used range loss to characterize climate exposure, and assigned scores from 0 to 3 in increasing order to range losses of 0–25, 25–50, 50–75, and 75–100%. We used the ratio of range gain to loss to characterize climate sensitivity and adaptive capacity, and assigned scores between 0 and 3 again in increasing order when the ratio of projected range gain to loss was >2:1, 1–2:1, 0.5–1:1, and 0–0.5:1. The two scores were then summed for a final vulnerability score

We treated the number of times in which the vulnerability score agreed across individual GCMs and the multimodel average as a measure of agreement in the assessment. For comparison, we completed the vulnerability assessment in the breeding season using maps that were not clipped by dispersal limits. Also, we calculated a vulnerability index that included vulnerability scores based on current population size and current breeding and nonbreeding range sizes from the Partners in Flight Landbird Conservation Plan (Rosenberg et al., 2016). We describe the methods for this alternative metric in Supporting Information.

3 | RESULTS

Nearly half (42%) of grassland birds were highly vulnerable during the breeding season under 3.0°C increase in global mean temperature scenario (Figure 3 and Table 2). This proportion declined to 13% with a 2.0°C increase and to 8% with a 1.5°C increase. More than 70% of grassland birds exhibited some degree of vulnerability during the breeding season under the 3.0°C (76%) and 2.0 and 1.5°C (71%) scenarios, such that the number of neutral species remained relatively constant (24–29%). In the nonbreeding season, climate change vulnerability was much lower with 3–6% of species highly vulnerable and 41–44% classified as neutral across all scenarios.

Declining sensitivity to climate change contributed more than changes in adaptive capacity to lower vulnerability scores under reduced exposure scenarios (Figure 4). As evidence, the correlation between sensitivity and adaptive capacity scores in the breeding season was highest for the 3.0°C increase in global mean temperature scenario and declined with reduced exposure to warming. A similar, but less pronounced, pattern occurred in the nonbreeding season. In addition, the proportion of species with declining sensitivity scores (66 and 26% in breeding/nonbreeding) across scenarios exceeded the proportion with declining adaptive capacity scores (38 and 12% in breeding/nonbreeding).

Three species were highly vulnerable regardless of scenario: Henslow's sparrow (*Ammodramus henslowii*) and McCown's longspur (*R. mccownii*) in the breeding season and Baird's sparrow (*Ammodramus bairdii*) in both seasons (Table 2 and Figure 5). Seven species were projected to lose more than 95% of their modeled current distribution, including those listed above plus Bobolink (*Dolichonyx oryzivorus*), Chestnut-collared Longspur (*Calcarius ornatus*), LeConte's sparrow (*Ammodramus leconteii*), and Sprague's pipit (*Anthus spragueii*).

We assessed the agreement in assigning climate change vulnerability classes between the multimodel ensemble and three individual GCMs representing a range of climate futures for North America. Agreement was generally high and increased with the magnitude of projected climate change. In the breeding season, 87–95% of species had

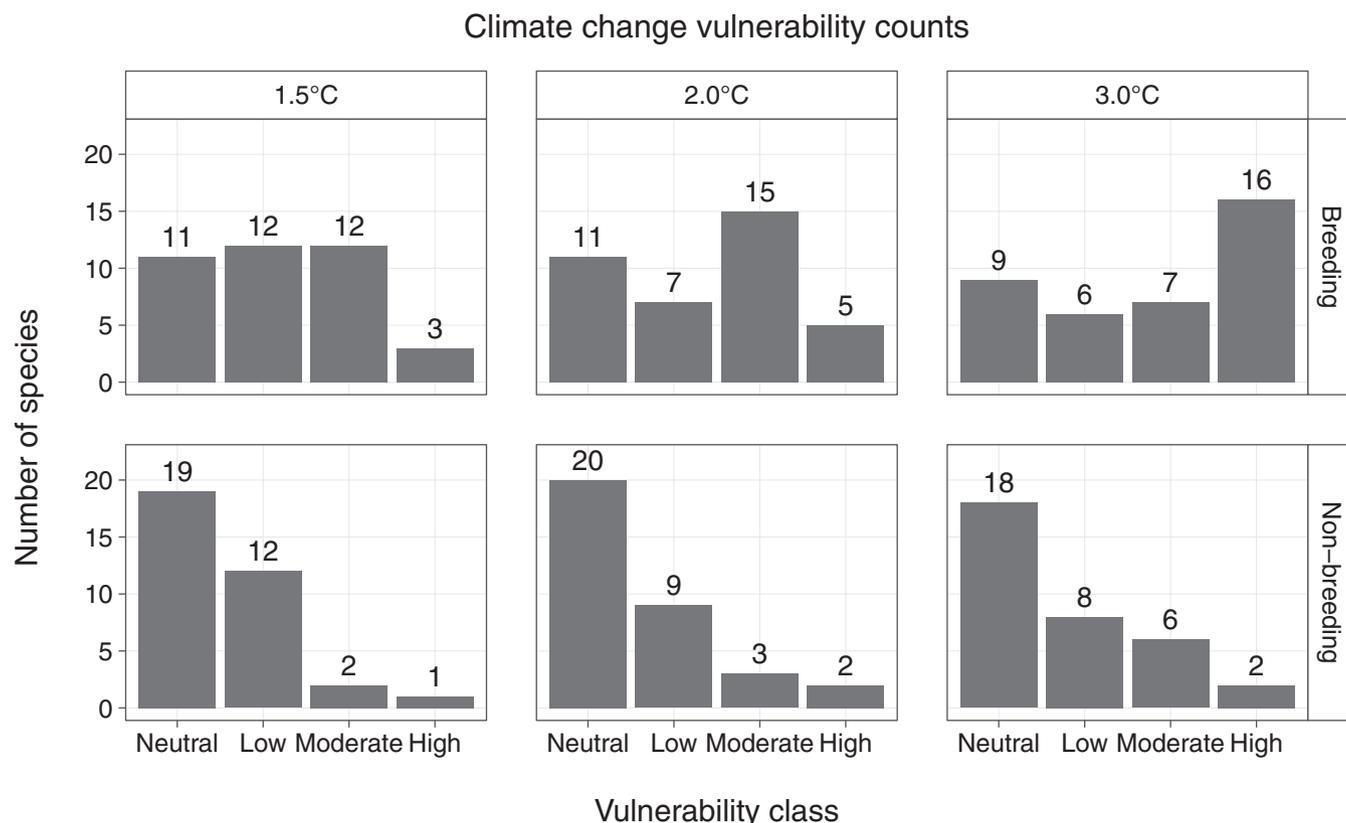


FIGURE 3 Climate change vulnerability assessment of 38 species of grassland birds under three scenarios for projected future mean global temperature rise

TABLE 2 Climate change vulnerability scores and agreement across scenarios by species. Vulnerability is assessed as Neutral (N), Low (L), Moderate (M), or High (H). Agreement is assessed as Low (L), Moderately Low (M-L), Moderately High (M-H), or High (H)

Common name	Scientific name	Season	Vulnerability			Agreement		
			1.5° C	2.0° C	3.0° C	1.5° C	2.0° C	3.0° C
Aplomado falcon	<i>Falco femoralis</i>	Breeding	L	L	H	M-H	M-H	M-H
		Nonbreeding	M	M	M	H	M-H	M-H
Baird's sparrow	<i>Ammodramus bairdii</i>	Breeding	H	H	H	M-H	H	H
		Nonbreeding	H	H	H	H	H	H
Bobolink	<i>Dolichonyx oryzivorus</i>	Breeding	M	M	H	M-H	H	M-H
Botteri's sparrow	<i>Peucaea botterii</i>	Breeding	M	M	H	H	H	M-H
		Nonbreeding	N	N	L	M-H	M-H	M-H
Burrowing owl	<i>Athene cunicularia</i>	Breeding	N	N	N	M-H	M-H	M-H
		Nonbreeding	N	N	N	M-H	H	M-H
Cassin's sparrow	<i>Peucaea cassinii</i>	Breeding	N	N	L	M-H	M-H	M-H
		Nonbreeding	L	M	M	M-H	M-H	M-H
Chestnut-collared longspur	<i>Calcarius ornatus</i>	Breeding	M	H	H	L	M-H	H
		Nonbreeding	L	M	M	M-H	M-H	M-H
Clay-colored sparrow	<i>Spizella pallida</i>	Breeding	M	M	H	M-H	M-H	M-H
		Nonbreeding	N	N	N	H	H	H
Dickcissel	<i>Spiza americana</i>	Breeding	N	N	N	H	H	H
		Nonbreeding	N	N	N	H	H	H
Eastern kingbird	<i>Tyrannus tyrannus</i>	Breeding	L	M	M	M-H	M-H	M-H
Eastern meadowlark	<i>Sturnella magna</i>	Breeding	L	L	M	H	M-H	H
		Nonbreeding	N	N	N	M-H	H	H
Ferruginous hawk	<i>Buteo regalis</i>	Breeding	L	M	M	M-L	M-L	M-H
		Nonbreeding	L	L	M	M-L	M-H	M-H
Grasshopper sparrow	<i>Ammodramus savannarum</i>	Breeding	N	N	L	M-H	M-H	M-H
		Nonbreeding	N	N	N	M-H	M-H	H
Gray partridge	<i>Perdix perdix</i>	Breeding	M	M	H	M-H	H	M-H
		Nonbreeding	L	L	L	M-H	M-H	M-H
Greater prairie-chicken	<i>Tympanuchus cupido</i>	Breeding	M	L	N	H	M-H	M-H
		Nonbreeding	N	N	N	M-H	H	H
Henslow's sparrow	<i>Ammodramus henslowii</i>	Breeding	H	H	H	M-H	H	H
		Nonbreeding	N	N	N	H	H	H
Horned lark	<i>Eremophila alpestris</i>	Breeding	L	L	L	M-H	M-H	M-L
		Nonbreeding	L	L	L	H	H	H
Lark bunting	<i>Calamospiza melanocorys</i>	Breeding	L	M	H	M-H	M-H	M-H
		Nonbreeding	L	N	N	H	M-H	M-H
Le Conte's sparrow	<i>Ammodramus leconteii</i>	Breeding	M	M	H	M-H	M-H	M-H
		Nonbreeding	N	N	N	H	H	H
Lesser prairie-chicken	<i>Tympanuchus pallidicinctus</i>	Breeding	L	L	M	M-H	H	H
		Nonbreeding	N	L	L	M-H	M-H	M-H
Loggerhead shrike	<i>Lanius ludovicianus</i>	Breeding	N	N	N	M-H	M-H	M-H
		Nonbreeding	N	N	N	H	M-H	M-H
Long-billed curlew	<i>Numenius americanus</i>	Breeding	M	M	H	M-H	M-H	M-H
		Nonbreeding	N	N	N	M-H	M-H	H
McCown's longspur	<i>Rhynchophanes mccownii</i>	Breeding	H	H	H	M-H	M-H	M-H
		Nonbreeding	L	L	M	H	H	H
Mountain plover	<i>Charadrius montanus</i>	Breeding	M	H	H	M-L	M-H	H
		Nonbreeding	L	L	L	H	H	H
Nelson's sparrow	<i>Ammodramus nelsoni</i>	Breeding	L	M	H	M-L	M-L	M-L
		Nonbreeding	M	H	H	M-H	M-L	M-H
Northern bobwhite	<i>Colinus virginianus</i>	Breeding	N	N	N	H	H	H
		Nonbreeding	N	N	N	M-H	M-H	H

TABLE 2 (Continued)

Common name	Scientific name	Season	Vulnerability			Agreement		
			1.5°C	2.0°C	3.0°C	1.5°C	2.0°C	3.0°C
Ring-necked pheasant	<i>Phasianus colchicus</i>	Breeding	N	N	L	M-H	H	M-H
		Nonbreeding	L	L	L	M-H	M-H	M-H
Savannah sparrow	<i>Passerculus sandwichensis</i>	Breeding	M	M	H	M-H	M-H	M-H
		Nonbreeding	L	L	L	H	H	H
Scissor-tailed flycatcher	<i>Tyrannus forficatus</i>	Breeding	N	N	N	H	H	H
		Nonbreeding	N	N	N	H	H	H
Sedge wren	<i>Cistothorus platensis</i>	Breeding	M	M	M	M-H	M-H	M-H
		Nonbreeding	L	N	N	H	M-H	M-H
Sharp-tailed grouse	<i>Tympanuchus phasianellus</i>	Breeding	L	L	L	M-H	M-H	M-H
		Nonbreeding	L	L	M	H	H	M-L
Short-eared owl	<i>Asio flammeus</i>	Breeding	M	M	M	M-H	M-H	H
		Nonbreeding	N	N	L	H	H	M-H
Sprague's pipit	<i>Anthus spragueii</i>	Breeding	L	M	H	M-L	M-L	M-H
		Nonbreeding	N	N	N	M-H	H	H
Swainson's hawk	<i>Buteo swainsoni</i>	Breeding	N	N	N	M-H	M-H	M-H
Upland sandpiper	<i>Bartramia longicauda</i>	Breeding	N	N	N	H	H	M-H
Vesper sparrow	<i>Poocetes gramineus</i>	Breeding	L	M	M	M-H	M-L	M-H
		Nonbreeding	N	N	N	H	H	M-H
Western kingbird	<i>Tyrannus verticalis</i>	Breeding	N	N	N	H	H	H
		Nonbreeding	N	N	N	M-H	M-H	M-H
Western meadowlark	<i>Sturnella neglecta</i>	Breeding	L	L	L	M-H	H	H
		Nonbreeding	N	N	N	M-H	H	H

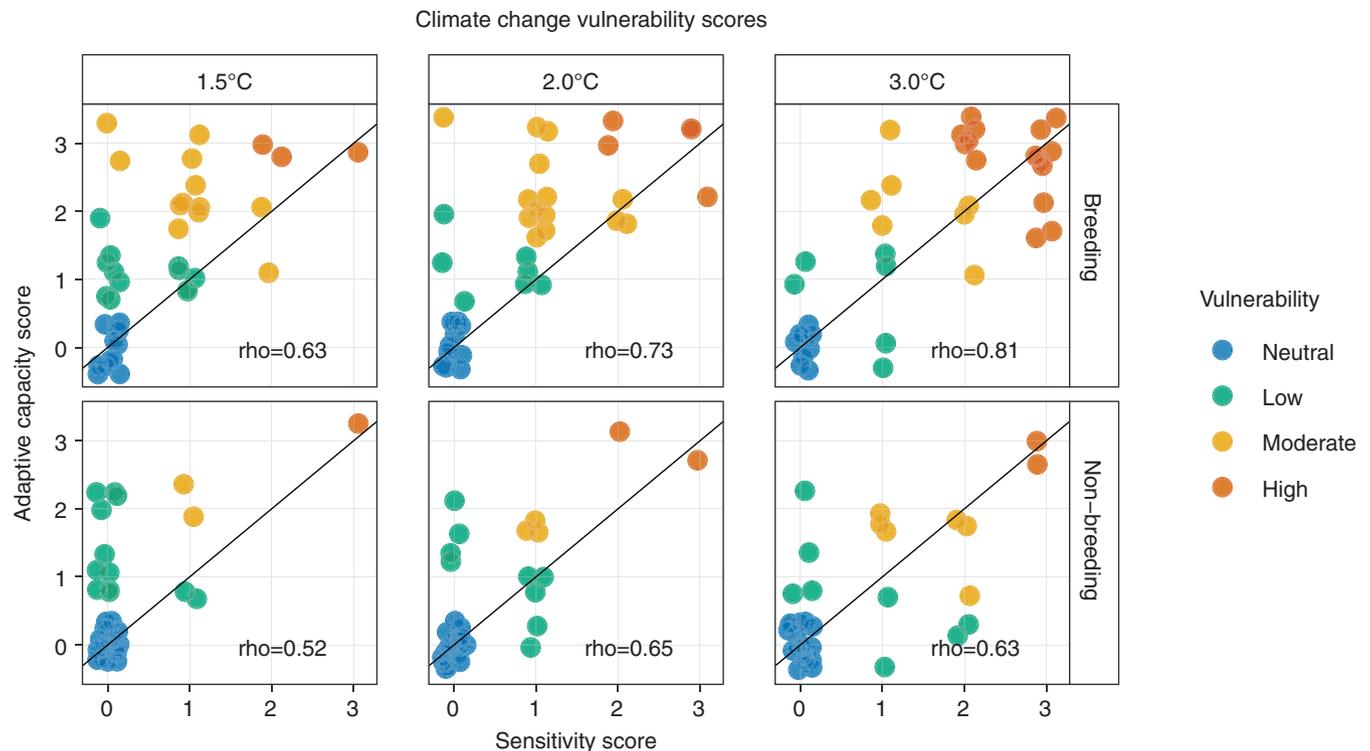


FIGURE 4 Spearman's rank correlation (rho) between climate change exposure and sensitivity/adaptive capacity scores

medium-high or high agreement across all scenarios. In the nonbreeding season, 97% of species had medium-high to high agreement regardless of scenario.

Including dispersal limitations increased the vulnerability of species. Breeding season vulnerability scores were generally lower when recalculated without restricting potential

Projected range change for Baird's Sparrow

Loss Stable Gain

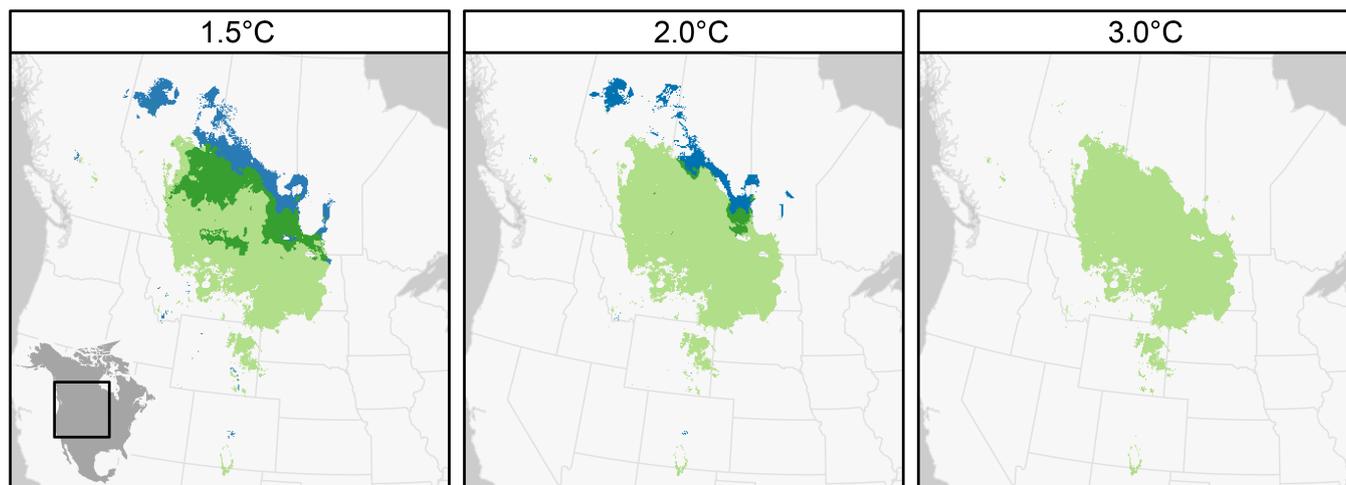


FIGURE 5 Projected range change for Baird's sparrow (*Ammodramus bairdii*) under three scenarios for increase in global mean temperature

range gains by dispersal capacity, with 32, 24, and 11% of species highly vulnerable under the 3.0, 2.0, and 1.5°C increase in global mean temperature scenarios, respectively. Meanwhile, the proportion of neutral species (24–32%) remained similar (Supporting Information, Appendix 2). In addition, climate change vulnerability scores were robust to an alternative index that incorporated information on current population and range size available for 33 species (see Appendix 2 in Supporting Information). Under the alternative index, 1–6 (3–18%) highly vulnerable species across scenarios dropped to moderately vulnerable in the breeding season, but did not change in the nonbreeding season. The vulnerability of four (12%) species in the breeding season and eight species (27%) in the nonbreeding season increased from neutral to low.

Final distribution models performed well predicting to spatially independent test datasets. Median AUC across species models was 0.93 (IQR: 0.87–0.96) in summer and 0.92 (IQR: 0.87–0.95) in winter (see Appendices 2 & 3 in Supporting Information for more performance results). Median true presence rates (0.90) exceeded median true negative rates (0.84), suggesting that models on average defined suitability broadly to include 90% of all known presence grid cells. Mean annual precipitation (MAP) was consistently among the most important predictor variables across species in summer, followed by chilling degree days (DD₀) and mean temperature of the warmest month (MWM_T, see Appendices 2 and 3 in Supporting Information for more results on variable influence). Precipitation as snow (PAS) was consistently among the most important predictor variables in winter, followed by Climatic moisture deficit (CMD).

4 | DISCUSSION

Grasslands are critically endangered globally and an irreplaceable ecoregion in North America, yet habitat

conversion continues at high rates. We show that climate change is an emerging threat to grassland birds and that current climate change policy commitments are insufficient. The Paris Agreement framework includes pledged reductions in greenhouse gas emissions (i.e., Nationally Determined Contributions) leading to an estimated 3.2°C global increase in mean temperature (Climate Transparency, 2018; UN, 2016). Even if these stated goals are achieved, nearly half of grassland bird species will remain highly vulnerable to climate change. The IPCC has identified a 2.0°C increase in global mean temperature as the target to avoid catastrophic impacts of climate change on human and natural systems (IPCC, 2013) and recently identified warming of 1.5°C as virtually inevitable by 2030–2052 (IPCC, 2018). Already in 2017, there was a +1.3°C global land temperature anomaly (NOAA National Centers for Environmental Information [NCEI], 2018). Our results provide compelling evidence that for grassland birds there is notable benefit to taking action to reduce warming from a 3.0 to a 2.0°C increase in global mean temperature, because it would reduce the proportion of highly vulnerable birds from 42 to 13%. To do this, we need rapid and aggressive emissions reductions.

Nine North American grassland bird species included in this analysis are species of continental conservation concern (Rosenberg et al., 2016). Of those, seven are highly vulnerable in at least one season under the scenario for a 3°C increase in global mean temperature (Appendix 2, Table S2). That becomes six species with a 2°C increase, and three species with a 1.5°C increase. Thus, policies that reduce climate change will also benefit the most at-risk grasslands species.

A few CCVAs have been conducted on grassland birds in North America. These include trait-based assessments conducted at continental (NABCI, 2010) and global scales (Foden et al., 2013) as well as model-based assessments (Langham et al., 2015). Trait-based approaches suggested

moderate to low vulnerability for grasslands species in the United States (NABCI, 2010), or high vulnerability for 5 (13%) of the 38 grassland species included in this analysis (Foden et al., 2013). Langham et al. (2015) identified 32% of grassland birds in the United States and Canada as highly vulnerable and 21% as moderately vulnerable. Our vulnerability assessment expanded on existing grassland bird CCVAs by combining trait- and model-based approaches, and our results suggest that previous assessments may under-estimate vulnerability.

This work stands out from previous efforts for the volume of observation data included, and the extensive use of spatially structured data partitioning and filtering to improve model performance and transferability (Radosavljevic & Anderson, 2014; Veloz, 2009; Wenger & Olden, 2012). However, the use of citizen science datasets in this assessment and the discrepancies in protocols across datasets may violate some assumptions of the Maxent and boosted regression tree models used, resulting in biased models (Yackulic et al., 2013). In spite of having millions of observation records, not every grid cell was sampled and there was spatial bias (primarily toward population centers) in those that were sampled. In addition, individual species' detection probabilities across species and datasets were not equal to one and detection was not modeled explicitly, as is common when modeling occurrence, as opposed to occupancy or abundance. We acknowledge these limitations, but took steps described in the methods to minimize their impact. These included target-group background sampling, data filtering, and spatially stratified cross-validation to address biases. Also, we chose to model suitability using presence-only methods, instead of occupancy or relative abundance, because of the inevitable variation in detection probabilities across datasets, with field conditions (which are unknown and not considered in our models), and across vegetation types. Changes in suitability using the species distribution model approach correlate with changes in relative abundance across large geographic regions (Stephens et al., 2016). The methods we employed are common practice in the Maxent and species distribution modeling literature (Radosavljevic & Anderson, 2014). However, it is possible that alternative approaches, such as distance null-model calibrated AUC (Hijmans, 2012), may further improve model transferability in future species distribution modeling efforts.

Inclusion of vegetation and land-use covariates may also be sources of error. First, vegetation projections were not mechanistic and therefore do not reflect the dynamics of plant range expansion and contraction, likely overestimating future range gains and under-estimating vulnerability (Stralberg et al., 2015). Furthermore, vegetation projections were based on CMIP3 climate projections, which differ from the CMIP5 projections used for climate covariates. CMIP5 is considered to have improved performance over CMIP3; but the similarities in the projections exceed the differences

(Sun, Stevens, Buddenberg, Dobson, & Easterling, 2015). The fact that the vegetation classifications were consensus projections across multiple GCMs and emissions scenarios may result in under-estimation of vegetation change under the 3°C increase scenario and over-estimating vegetation change under the 1.5°C increase scenario. The challenge of finding vegetation projections at broad spatial scales lead many to exclude vegetation from distribution projections (Langham et al., 2015; Lawler et al., 2009; Stralberg et al., 2015), to use general assumptions about vegetation lag-times (Stralberg, Bayne, et al., 2015), or to work with regional projections (Matthews, Iverson, Prasad, & Peters, 2011). We opted to include vegetation despite the limitations of available data. Vegetation was among the top predictors for only five (13%) and six (15%) species in the breeding and non-breeding seasons (Appendix 2), suggesting the impact of the variable was generally small. Vegetation was the single most important variable for *Anthus spragueii* and *Calcarius ornatus*. However, both of these were already two of the most vulnerable species, so under-estimation of vegetation change under the 3.0°C increase scenario would not have changed their vulnerability classification. Finally, projected land-use change was not incorporated, likely leading to additional over-estimation of range sizes.

Combined model- and trait-based vulnerability assessments are an improvement on single-method approaches, but information gaps remain. Our model-based approach infers potential for range expansion (i.e., colonization) or contraction (i.e., extirpation) based on suitability and dispersal potential, but we did not model colonization or extirpation processes directly (Yackulic, Nichols, Reid, & Der, 2015). This can lead to errors, particularly if colonization and extinction probability respond to covariates that differ from those used in our distribution models (Yackulic et al., 2015). Furthermore, some species could adjust breeding phenology to increase their adaptive capacity to climate change beyond the projected range shifts modeled here (Socolar, Epanchin, Beissinger, & Tingley, 2017). Species' distributions may also be impacted by factors other than climate, such as inter-specific interactions (Zarnetske, Skelly, & Urban, 2012), which were not assessed here. Finally, in spite of including >40 datasets, 10 species had fewer than 50 grid cells with which to build a distribution model (Appendix 3). All but one of these are winter distributions concentrated in Mexico. Model performance was still acceptable in spatially stratified cross validation (e.g., >70% presences correct) and similar models have been published elsewhere (Costa et al., 2010), but more occurrence data would improve the confidence in the vulnerability assessment for these species.

Finally, it is relevant to note that there is a potentially synergistic effect between climate policies to reduce greenhouse gas emissions and land-use impacting grasslands. Policies that advocate for the expansion of renewable fuels may result in grassland conversion. For example, renewable fuel

standards resulted in higher rates of grassland conversion regionally, including 1.5 million ha of converted grasslands within 100 miles of refineries in the Midwestern United States (Wright, Larson, Lark, & Gibbs, 2017). This occurred in spite of the existence of voluntary programs for grassland conservation in the United States like the Conservation Reserve Program (www.fsa.usda.gov), the Agricultural Conservation Easement Program, and the Crop Production on Native Sod program (www.ers.usda.gov), which have helped stabilize the decline in grassland bird populations (NABCI, 2017). Most present-day grasslands conversion are lands taken out of CRP (Lark et al., 2015; Morefield, LeDuc, Clark, & Iovanna, 2016) highlighting the precarious nature of conservation gains from voluntary programs (Wright et al., 2017). Programs like the Land and Water Conservation Fund (www.doi.gov/lwcf), which distributes federal revenue from oil and gas development to land conservation programs that include acquisitions, easements, and enhancements of grasslands among other habitats, may be more effective at protecting grasslands. Lessons can be learned from the Amazon where programs that linked payments for ecosystem services (e.g., carbon credits) with anti-deforestation campaigns were most successful (Nepstad et al., 2014) at reducing deforestation.

In conclusion, this work represents a comprehensive effort at assessing climate change vulnerability for an at-risk species group. Nearly one-half of grassland birds are highly vulnerable to climate change under our current global greenhouse gas emissions trajectory. Grassland birds need aggressive policy action to reduce greenhouse gas emissions while continuing to limit additional grassland conversion.

ACKNOWLEDGMENTS

The John D. and Catherine T. MacArthur Foundation, grant G-1511-150388, and the USDA Natural Resources Conservation Service, grant 69-3A75-17-320, funded this work. We also thank all of the institutions and partners that provided data for this analysis (listed in Supporting Information), as well as all of the thousands of volunteer participants who gathered data for these projects. To the extent possible, this research was completed in compliance with the *Guidelines to the Use of Wild Birds in Research*; however, the authors were not directly involved in the collection of the datasets used.

CONFLICT OF INTEREST

The authors declare no conflicts of interest in the publication of this paper.

AUTHOR CONTRIBUTIONS

C.W., L.T., and G.L. conceived the study; L.T., C.J., and A.P. contributed to data preparation; C.W., L.T., B.B., and

N.M. contributed to the species distribution modeling and manuscript writing; C.W., L.T., and N.M. made revisions; and all authors reviewed, edited, and approved the final manuscript.

DATA ACCESSIBILITY

Datasets analyzed in this research were assembled from existing open (e.g., public) and closed avian data repositories. Publicly available bird observation data used for this assessment can be assembled from eBird, the USGS Breeding Bird Survey, and gbif. Climate and landcover data were assembled from AdaptWest and the CEC Environmental Atlas, respectively.

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SUPPORTING INFORMATION

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

How to cite this article: Wilsey C, Taylor L, Bateman B, et al. Climate policy action needed to reduce vulnerability of conservation-reliant grassland birds in North America. *Conservation Science and Practice*. 2019;1:e21. <https://doi.org/10.1111/csp2.21>