Biological Conservation 270 (2022) 109556

Contents lists available at ScienceDirect

Biological Conservation

journal homepage: www.elsevier.com/locate/biocon

Policy analysis

The potential of semi-structured citizen science data as a supplement for conservation decision-making: Validating the performance of eBird against targeted avian monitoring efforts[☆]

Erica F. Stuber[a,b,*], Orin J. Robinson[b], Emily R. Bjerre[c], Mark C. Otto[c], Brian A. Millsap[c], Guthrie S. Zimmerman[c], Michael G. Brasher[d], Kevin M. Ringelman[e], Auriel M.V. Fournier[f], Aaron Yetter[f], Jennifer E. Isola[g], Viviana Ruiz-Gutierrez[b]

[a] *U.S. Geological Survey Utah Cooperative Fish and Wildlife Research Unit, Department of Wildland Resources, Utah State University, Logan, UT, USA*
[b] *The Cornell Lab of Ornithology, Cornell University, Ithaca, NY, USA*
[c] *U.S. Fish and Wildlife Service, National Raptor Program, Division of Migratory Bird Management, Washington, DC, USA*
[d] *Ducks Unlimited, Inc., 1 Waterfowl Way, Memphis, TN, USA*
[e] *School of Renewable Natural Resources, Louisiana State University Agricultural Center, Baton Rouge, LA, USA*
[f] *Forbes Biological Station–Bellrose Waterfowl Research Center, Illinois Natural History Survey, Prairie Research Institute, University of Illinois at Urbana-Champaign, Havana, IL 62644, USA*
[g] *Sacramento National Wildlife Refuge Complex, U.S. Fish and Wildlife Service, 752 County Rd. 99W, Willows, CA, USA*

ARTICLE INFO

Keywords:
Bald eagle
Community science
Decision-making
Natural resource management
Policymaking
Waterfowl

ABSTRACT

Methods are being developed to capitalize on citizen science data for research and monitoring, but these data are rarely used within established decision-making frameworks of wildlife agencies. Citizen science data are often collected at higher resolution and extent than targeted monitoring programs, and may provide complementary information. Here, we demonstrate that carefully filtered semi-structured citizen science observations, when paired with targeted survey data, can produce ecological predictions at higher resolution and extent than targeted surveys alone, and both datasets can represent complementary aspects of species' ecology. We present case studies demonstrating how citizen science data can enhance or supplement decision-making of government and conservation organizations. First, we show how the continuous spatial coverage of citizen science projects, when coupled with targeted surveys, can improve estimates of metrics used by the U.S. Fish and Wildlife Service in regulatory processes to estimate population size, and inform take limits of federally managed species nationwide. Second, we show that the spatial coverage of citizen science accommodates dynamic avian space use patterns during key times of the year, relative to standardized monitoring protocols carried out by the Illinois Natural History Survey. Lastly, we demonstrate that citizen science information can replicate estimates of migratory chronologies for the Illinois Natural History Survey and the U.S. Fish and Wildlife Service for some waterfowl species, and in some contexts can supplement missing data on abundance. These findings illustrate the value of integrating validated information from semi-structured citizen science into the current evidence base used to justify, inform, and evaluate conservation decision-making.

1. Introduction

Conservation and management decisions are subject to increased levels of scrutiny, formal information requirements, and even legal mandates, and thus have typically been informed by targeted and statistically designed biological monitoring programs to provide data (e.g.,

* Corresponding author at: U.S. Geological Survey Utah Cooperative Fish and Wildlife Research Unit, Department of Wildland Resources, Utah State University, 5230 Old Main Hill, Logan, UT 84322, USA.
E-mail address: efstuber@gmail.com (E.F. Stuber).

https://doi.org/10.1016/j.biocon.2022.109556
Received 7 October 2021; Received in revised form 18 March 2022; Accepted 10 April 2022
Available online 6 May 2022

Nichols and Williams, 2006). However, managers often have limited resources with which to meet their mandate of maintaining wildlife in the public trust. This may include limited funding and human resources for collecting scientific data needed to inform management decisions, and targeted monitoring programs are, by definition, limited in spatial, temporal, and taxonomic scope.

There has been recent, rapid development in methodological techniques focused on addressing bias and sources of variation in data collected by global citizen scientists (here, we use the term citizen science (CS) sensu Cooper et al., 2021, and Shirk et al., 2012 to denote a form of science inclusive of any volunteer participant) (Johnston et al., 2022). As CS data collection has expanded into the 'Big Data' realm, there is currently an unprecedented opportunity for wildlife professionals to consider novel CS data streams within decision frameworks to support evidence-based conservation and allow for the implementation of proactive management actions. If high quality CS data are able to match the scientific findings generated by professional scientific monitoring programs (e.g., produce unbiased estimates of population attributes), wildlife professionals would have access to low cost, high-resolution data with the potential to partly overcome and fill critical data gaps, complementing traditional data sources and increasing the efficiency and effectiveness of management actions.

CS data are considered of high quality for scientific inference when species observations are recorded following semi-structured design (Kelling et al., 2019). Semi-structured data include ancillary information on the observation process such as precise location, time of day, completeness, skill level of the observer, and sampling effort (e.g., completeness (presence-absence versus presence-only), ability of the observer, effort expended; Yoccoz et al., 2001, Bonney et al., 2009, Johnston et al., 2022). Although management agencies have been successful in coordinating and using structured CS data collected under strict collection protocols and sampling design (e.g., the Pacific Northwest Bumble Bee Atlas coordinated by multiple state wildlife management agencies and a non-profit, https://www.pnwbumblebeeatlas.org/; the North American Breeding Bird Survey coordinated by multiple Federal agencies, https://www.pwrc.usgs.gov/bbs/about/; Snapshot Wisconsin coordinated by the Wisconsin Department of Natural Resources, https://dnr.wisconsin.gov/topic/research/projects/snapshot), the exponential growth of CS observations recorded within semi-structured projects is making it increasingly possible to access and incorporate a wealth of additional high-quality data in biological studies (e.g., eBird (Kelling et al., 2019), eButterfly (Prudic et al., 2017)). Because some CS databases house data collected at high spatial and temporal resolution and across great extents, once semi-structured CS data reach a critical mass, they may become highly valuable to conservation professionals and wildlife managers.

The most straightforward pathway from CS to evidence-based management decision-making is one based on data validation and strategic partnerships (e.g., Fig. 2 in: Ruiz-Gutierrez et al., 2021). Initially, research scientists with expertise working with CS data can connect with policy and decision makers, and collaborations can grow based on establishing trust and mutual commitment towards achieving common goals. Based on this two-way exchange, partners would aim to identify recurring information needs that feed into current policy design and decision-making frameworks, and information gaps that, if filled, could improve decision-making. Once management objectives, data needs, and relevant available CS data are identified, the team would attempt to validate CS information against accepted data sources or standards. In situations where CS adequately replicates findings from professional monitoring programs, CS information would be integrated into the decision-making framework. Once CS data have been appropriately validated, wildlife decision-makers would have an additional data stream that could be used to inform decisions. This may allow agencies to reallocate funds, extend biological coverage, or supplement data deficiencies (see Table 1 for examples).

Here, we present three case studies to demonstrate the process of validating if, where, and when CS information may act as a complementary data source to meet population objectives within targeted wildlife monitoring programs. By working as a cross-agency team that included management decision-makers and CS data-analysis, we were able to develop specific case studies to identify information needs and objectives for specific conservation and management programs, and identify where CS use could be most valuable. Understanding the contexts in which CS-based information can be used as a trusted and valid data source for evidence-based wildlife decision-making will allow organizations to enhance their information pipeline, improving the capacity to sustain natural resources and support proactive conservation planning.

Table 1
Additional resource allocation options available to conservation and management agencies once citizen science data have been validated for use within targeted monitoring programs. In this context, validation of CS data refers to the process of establishing evidence that CS data accurately represent similar information as that gathered from within professional, often targeted surveys, for a specific purpose.

CS-enabled option	Description	Example
Extend	Extend the scientific evidence base to include unstudied species or locations without dedicating agency resources	Use validated CS data for previously data deficient species; integrate validated CS data to extend the coverage of targeted surveys
Reallocate	Reallocate resources by supplementing agency-run studies	Continue targeted surveys where CS cannot be validated, and reallocate resources away from environments where CS performs well
Supplement	Supplement professional surveys with missing data with CS	Citizen science projects may continue to operate even when national wildlife surveys have been cancelled, for example during federal furloughs

2. Methods

Because the analytical frameworks for our case studies follow the same general pattern, we present a general description of methods here and direct interested readers to Supplementary materials A1 and A2 for case-specific details.

2.1. Partnerships and objectives

2.1.1. U.S. Fish and Wildlife Service – National Raptor Program (FWS-NRP)

We partnered with the FWS-NRP to identify data requirements within the context of their framework for managing take of bald eagles (*Haliaeetus leucocephalus*). To implement the FWS eagle take permit program, the FWS-NRP estimates the number of occupied nesting territories of eagles across the coterminous USA every 3 years based on targeted, double-observer aerial surveys across specific areas within their high population density study region (U.S. Fish and Wildlife Service, 2009a). The number of estimated occupied nesting territories is then extrapolated out to the coterminous USA to generate an estimate of the total number of nesting territories. This estimate is adjusted by information from an integrated population model to calculate total number of birds, which is then used in a prescribed take level framework (Zimmerman et al., 2022). Because the FWS-NRP's aerial surveys for eagle nests are spatially restricted to expected high-density areas, in 2009 FWS-NRP relied on individual state surveys to enumerate a minimum population size in the coterminous USA outside of the high-density strata. Efforts to monitor bald eagles by individual states is declining, so for the most recent survey the FWS-NRP wanted to explore the potential of CS data from eBird, where data collection is unrestricted, to inform spatially continuous estimates and at higher spatial resolution. Using the most recent FWS-NRP survey data, collected during 2018–2019, we aimed to develop a model using relative abundance predictions from 2018 developed by the eBird Status & Trends team using observations from the eBird CS project as a predictor of aerial-survey based estimates of number of occupied nesting territories. In addition to representing a higher spatial resolution estimate of bald eagle numbers (i.e., 2.5km^2 resolution), the eBird-based relative abundance product represents the relative total number of bald eagles (i.e., including juveniles, adults, and floaters). Because of the mismatch in the units of measure between the two information sources, a statistical model was needed to identify whether a systematic relationship could be identified between the two related products (see Supplementary material A1.1 for model development details). If the eBird relative abundance product represented an accurate predictor of FWS-NRP's aerial survey data (i.e., validated), we could have greater confidence in our predictions outside of the FWS-NRP's aerial survey region as eBird observations are collected across the United States.

2.1.2. Illinois Natural History Survey (INHS) and U.S. Fish and Wildlife Service – Sacramento National Wildlife Refuge Complex (FWS-SNWRC)

The long-standing systematic approach for developing spatially explicit population objectives for waterfowl during the non-breeding period across North America was recently updated with new methods for parsing waterfowl distributions (Fleming et al., 2017, 2019). Despite this advancement, continental planning for non-breeding waterfowl continues to rely on migration chronologies derived from independent, local or regional-scale surveys to characterize temporal patterns of waterfowl abundance during autumn–winter. Migration chronologies are particularly important because the shape of the migration curve is one of the most sensitive parameters in determining period-specific and overall energetic demand during autumn–winter (Ringelman et al., 2018). Coordinated inter-regional planning to meet the needs of highly mobile, shared populations of migratory waterfowl is likely to be most effective when informed by common or similar phenological models capable of reliably depicting temporal patterns of waterfowl abundance across multiple planning scales (e.g., Joint Venture, Bird Conservation Regions) and regions. Presently, no such common models have been evaluated or implemented for inter-regional planning of this nature. Here, we evaluate the efficacy of using the eBird relative abundance product developed by the eBird Status & Trends team to generate migration chronologies, and investigate the relationship between relative abundance estimates and targeted surveys managed by the INHS and FWS-SNWRC. If eBird-based CS information can be demonstrated as a strong predictor of targeted survey metrics which are routinely collected by management agencies for application in waterfowl conservation planning models, it may serve as a consistent underlying source of data to seamlessly incorporate into large scale planning across multiple spatial scales and compensate for spatial and temporal data gaps.

2.2. Data

2.2.1. Management agencies' targeted surveys

Wildlife conservation agencies and researchers, such as FWS-NRP, INHS, and FWS-SNWRC, often use aerial or ground surveys to monitor population responses to environmental conditions or assess progress towards achieving management objectives. This information is generated by management agency partners, which have passed internal review (i.e., are accepted forms of data used to underlie management decisions). Because our aim is to use these data as response variables rather than to assess the accuracy of agency-collected data, we only briefly describe the data here, and direct interested readers to more thorough accounts of survey design and methods elsewhere (U.S. Fish and Wildlife Service, 2016b, U.S. Fish and Wildlife Service, 2019, Forbes Biological Station, 2020, Stafford et al., 2007, U.S. Fish and Wildlife Service, 2020b).

In our FWS-NRP case study, established aerial surveys are used to count occupied bald eagle nesting territories within 10×10 km^2 plots. The FWS-NRP Program conducts nationwide aerial surveys to estimate occupied bald eagle nesting territories, temporally restricted to the bald eagle breeding season, and spatially restricted to expected high-density areas. The survey design targets known nest locations and additional randomly selected survey plots, and accounts for detectability of nests by using a double-observer protocol. The "dual-frame" survey design enables estimation of the number of occupied nesting territories by combining information on the number of known nest locations, which is provided by individual states (the 'list frame') and estimating the number of additional occupied nests not accounted for by the lists (the 'area frame'). The number of newly identified, occupied nests is added to those from the list frame, and after accounting for imperfect detection, the FWS-NRP estimated the mean number of expected nests within survey sites (U.S. Fish and Wildlife Service, 2016b).

In our INHS and FWS-SNWRC case studies, waterfowl are counted along established transects at historical wintering locations, or complete counts of waterfowl are made within individual wetland unit boundaries and are aggregated to larger spatial extents (i.e., regions or counties). The INHS conducts aerial waterfowl counts at survey sites along the Illinois and central Mississippi Rivers, representing four management regions (Fig. 1), weekly, from September to May. Observers record the abundance of all waterfowl species present (Forbes Biological Station, 2020). The FWS-SNWRC conducts ground surveys on six federal refuges in four counties within the Sacramento Valley (Fig. 2) by vehicle, monthly, year-round for waterfowl (U.S. Fish and Wildlife Service, 2019). We selected six target waterfowl species (Mallard (*Anas platyrhynchos*), Northern Shoveler (*Spatula clypeata*), Green-winged Teal (*Anas crecca*), Northern Pintail (*Anas acuta*), Gadwall (*Mareca strepera*), Ring-necked Duck (*Aythya collaris*)) from each survey for our waterfowl case studies to represent variation in life histories and timing of migration.

In both case study scenarios we expect our results to only hold for the eBird relative abundance products used in the presented analyses. The eBird Status and Trends team periodically update the methods used internally to produce relative abundance maps, and depending on the scope of methodological updates, eBird relative abundance products for the same species in different years may not be directly comparable. In the case of a substantial methodological change, the analyses presented here would be re-run to make inference on other years of data. Because of the dynamic nature of eBird Status & Trends products, the results presented here are specific to the data product used, and should not be transferred to other times or locations uncritically.

2.2.2. CS data products: eBird-based relative abundance predictions

eBird is a global bird monitoring platform where hundreds of thousands of observers deposit millions of records of bird sightings annually. The eBird Status & Trends Project team housed within the Cornell Lab of Ornithology has generated weekly predictions of species' geographic range, occurrence rate, relative abundance, and population trends over time based on statistical modeling of various subsets of raw eBird data (Fink et al., 2020a). The Team has produced these products for ~100 species for the western hemisphere in the first release during 2017, 512 species in 2018, and over 800 species in 2021, with plans to increase coverage and availability on an annual basis. Here, we chose to use the relative abundance product developed by the Status & Trends Project team (hereafter referred to as: eBird relative abundance product) for our case studies as the units (i.e., predicted relative abundance, the expected "count of individuals of a given species detected by an expert eBirder at the optimal time of day, while expending the effort necessary to maximize detection of the species" from: https://ebird.org/science/status-and-trends/faq#mean-relative-abundance) most closely match those of the professional surveys (i.e., abundance of occupied nesting territories or waterfowl).

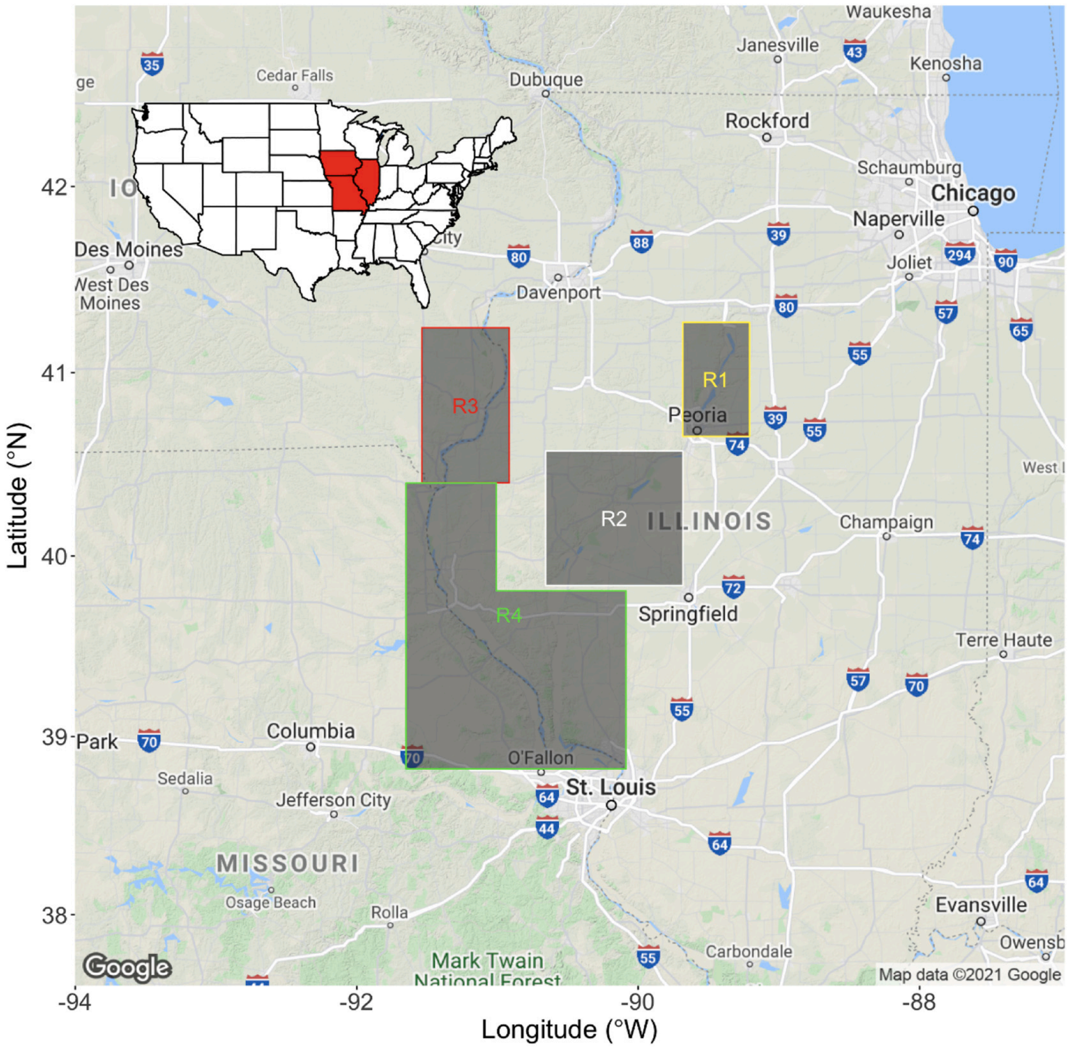

Fig. 1. Map of the Illinois Natural History Survey management regions in which aerial surveys and the relative abundance product developed by the eBird Status & Trends team were compared.

The underlying relative abundance predictions were generated based on carefully curated eBird data entries, high resolution environmental covariates, and statistical techniques suited for large scale spatio-temporal distribution modeling (Fink et al., 2020b). The eBird Status & Trends Project team only publishes products for species with adequate data coverage, that meet statistical inferential standards, and only after passing general, expert-review (for full details see https://ebird.org/science/status-and-trends/faq).

2.2.3. Validating CS data products

While the goal of our case studies was to compare CS-based information against targeted survey data, the different objectives of each management agency resulted in modified approaches for the validation process. For the objectives of the FWS-NRP (e.g., increase spatial resolution, extrapolate to unsampled areas), we developed predictive models of mean occupied nesting territories within 10 km^2 aerial survey sites in a regression-framework using the eBird relative abundance product as a predictor (2.5 km^2 resolution aggregated to 10 km^2 by summing; see Supplementary material A), and validated its performance in predicting unmeasured locations using k-fold cross validation on spatially stratified holdout data (see Supplementary material A1.1 for bald eagle model justification and specification). The model structure was developed to reflect expectations of Poisson-distributed data with an identity link, forcing the intercept through zero (i.e., no nests expected if eBird abundance is zero), which allowed the model to be applied without alteration at arbitrary spatial scales as needed. We included the eBird relative abundance estimate as the only fixed effect, and included a random effect of Stratum (i.e., the 'survey region') to account for potential geographic differences in the relationship between eBird relative abundance and the mean number of nesting territories. Additionally, we performed variable selection to define the temporal range over which the weekly eBird relative abundance product best predicts the FWS-NRP estimated number of occupied nesting territories (see Supplementary material A1.1 for model details and specification). If we demonstrated the eBird relative abundance product to be a strong predictor of the number of occupied nesting territories with out-of-sample hold out data, we could use eBird relative abundance to predict the number of occupied nesting territories in areas that the FWS-NRP did not survey. To predict the expected mean number of occupied nesting territories within the 5 FWS Eagle Management Units (EMU) of interest, we first subset each EMU into polygons representing the FWS-based survey Strata (which have a random effect in our fitted model) and unsurveyed areas. If a polygon representing an FWS-surveyed stratum spanned multiple EMUs, the polygon was subset based on the spatial overlay of EMUs and surveyed strata. The remaining unsurveyed area within each EMU was represented by sometimes non-contiguous 'unsurveyed' polygons. We then extracted the sum of eBird relative abundance within each polygon. Then we applied our fitted model to the extracted data (i.e., we used our

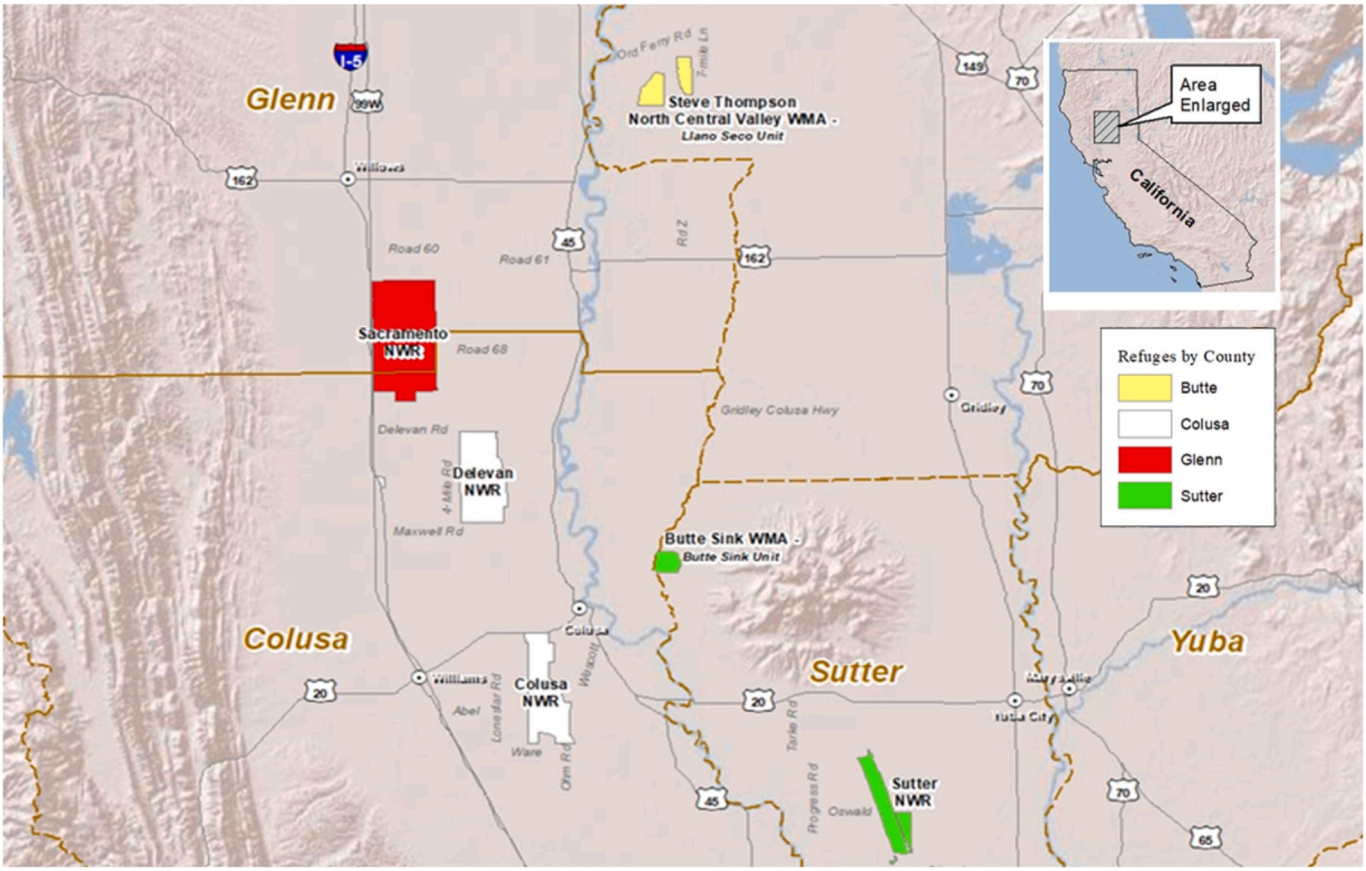

Fig. 2. Map of the U.S. Fish and Wildlife Service – Sacramento National Wildlife Refuge Complex management regions in which ground surveys and the relative abundance product developed by the eBird Status & Trends team were compared; Sacramento Valley, California.

model to predict the mean number of occupied nesting territories within each polygon of each EMU, accounting for the random effect of Stratum in relevant surveyed regions), and summed over all polygons within each EMU to obtain the EMU totals. The model formula for unsurveyed regions (i.e., regions not located within surveyed Strata) reduces to a fixed-effect-only equation (i.e., the random effect for polygons without an observed Stratum ID equals 1).

For the objectives of the INHS and FWS-SNWRC (e.g., describe temporal changes in waterfowl abundance within the survey region), we compared temporal trends in waterfowl abundance during 2018 across multiple species and spatial scales using a Spearman's correlation analysis to determine how closely each data set ranked the weekly abundance of each species at two spatial scales: the region, or county scale (INHS, and FWS-SNWRC, respectively) and the total study area extent scale (e.g., we determined whether the week or month with the highest abundance for 2018 (2nd highest, lowest, etc.) was the same in both data sets). This analysis represented concordance of migration chronologies between the two datasets. If the datasets were significantly correlated across the time period of the survey, we also developed generalized linear models of waterfowl abundance to evaluate whether the eBird relative abundance product covariate was a significant predictor of INHS or FWS-SNWRC count data and could substitute for instances of temporal missing data across geographic regions (e.g., in the case of a pandemic, Howell et al., 2022; for model description see Supplementary material A2.1).

3. Results

3.1. Bald eagle population monitoring

3.1.1. Cross-validation and variable selection

Variable selection identified week 21 (14 May–20 May) as the eBird relative abundance product week that had the best performance in predicting mean abundance of occupied nesting territories. With this week as a covariate our model predicted 1257 occupied nesting territories in spatial holdout data, which was only 1% higher than observed (1245 observed; Table 2). Predictive performance decreased monotonically when using any other eBird relative abundance product week,

Table 2
eBird relative abundance k-fold cross-validation predictions of occupied bald eagle nesting territories using spatial holdout data. Week 21, denoted in bold, was selected as the best performing week covariate and used in subsequent predictive modeling.

eBird week[a]	Predicted	Actual	Difference[b]
19	1114	1245	−131
20	1198	1245	−47
21	**1257**	**1245**	**12**
22	1371	1245	126
23	1433	1245	188
24	1516	1245	271
25	1543	1245	298

[a] Date of eBird relative abundance predictions used in model during variable selection procedure; eBird relative abundance products were produced at 2.5km^2 and weekly resolution throughout the annual cycle.

[b] Difference between model-based predictions of nesting territories in holdout samples and observed number of territories in holdout samples.

consistently underpredicting when using weeks 19–20 and over-predicting when using weeks 22–25 as predictors (prediction error ranged from underpredicting by 10% to overpredicting by 24%; Table 2).

3.1.2. Eagle Management Unit-level predictions of occupied nesting territories

We fit our model as above with week 21 of the eBird relative abundance product as our covariate and using the full data set (i.e., without holding out any observations) to obtain the most precise coefficient estimate. Once fitted, we used the model coefficient estimates, and the eBird relative abundance values across the coterminous USA to project the model across the 5 EMUs of interest (e.g., predict the mean number of nesting territories in each EMU including across unsurveyed areas). We propagated coefficient estimation uncertainty to EMU-level predictions by calculating the predicted total number of occupied territories 10,000 times, using each iteration of the MCMC sampling procedure (i.e., for each MCMC iteration we have a separate coefficient estimate; instead of predicting based on the posterior median only, we account for coefficient uncertainty by summarizing over all possible coefficient estimates). Using this model, we predicted 19,074 occupied territories in the Atlantic EMU, 36,038 in the Mississippi EMU, 6867 in the Central EMU, 9488 in the Mid-Latitude Pacific EMU, and 1234 in the Southwest Pacific EMU (Fig. 3; Anderson and Padding, 2015; U.S. Fish and Wildlife Service, 2016a).

3.1.3. Management decision implications

Previously, the FWS-NRP have used their internal estimates of the number of nesting territories in high-density regions, coupled with individual State lists of known nests to determine the total number of

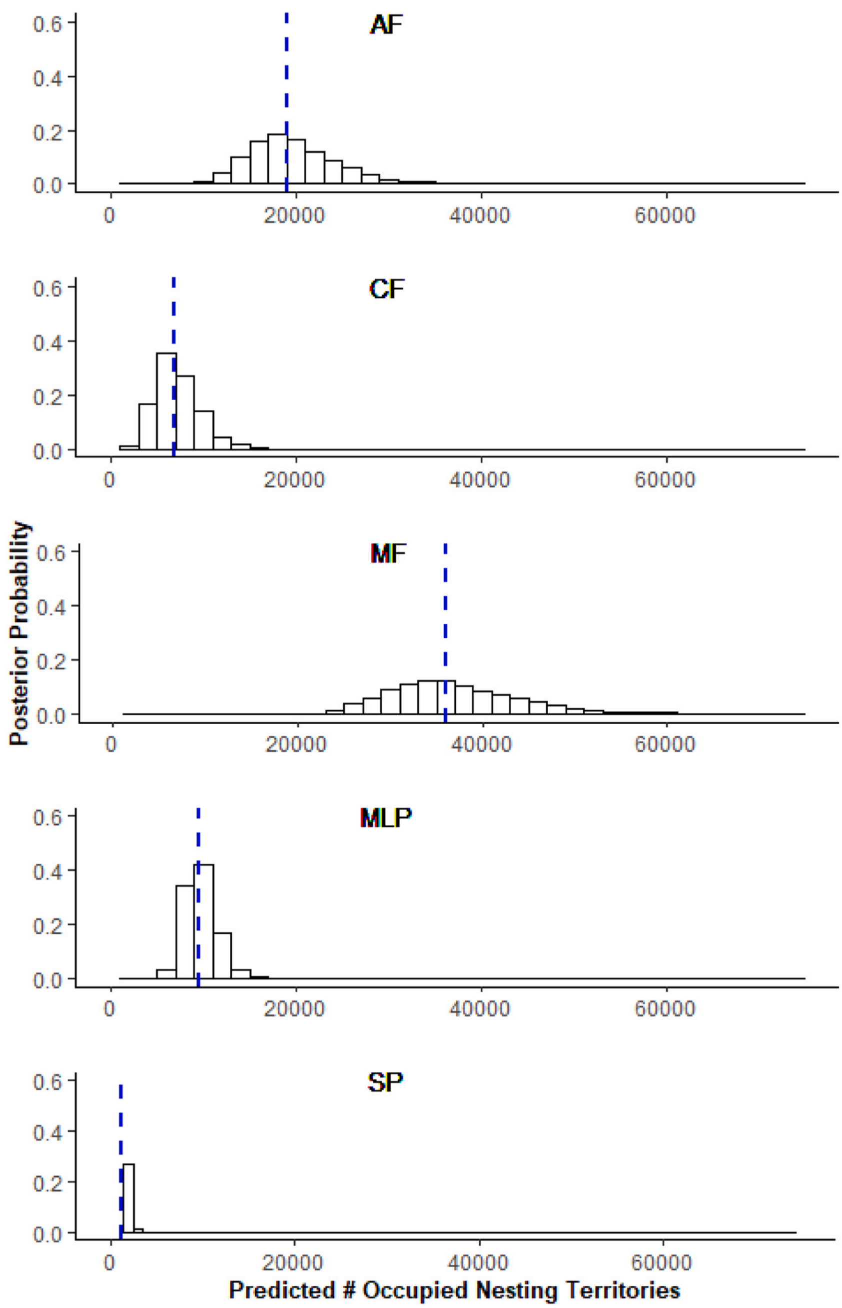

Fig. 3. Posterior predicted distributions of number of Bald eagle occupied nesting territories at the flyway scale. Dashed line indicates the median of the distribution. AF: Atlantic flyway; MF: Mississippi flyway; CF: Central flyway; MLP: Mid-latitude Pacific flyway; SP: Southwest Pacific flyway.

nesting territories across the coterminous USA. This estimate has been subsequently incorporated into population models to predict total population size (e.g., as in U.S. Fish and Wildlife Service 2016b). Because of resource and safety limitations, FWS-NRP had to accept the spatially restricted nature of their aerial survey design and the uncertainty associated with spatial extrapolation using only a list of occupied nesting territories known to State fish and wildlife agencies. Because we could create a highly accurate model to predict FWS-NRP survey-based information from CS-based information, where the underlying observation data is not spatially restricted, the FWS-NRP has decided to incorporate CS-based information into its planning frameworks. Based on this work, the FWS has now included predictions of the number of occupied nesting territories based on eBird relative abundance (i.e., that had been validated against FWS-NRP internal aerial survey data) into their calculations to determine total population size and population take limits which is included in a FWS technical report (U.S. Fish and Wildlife Service, 2020a). Because these results linking eBird information to aerial survey data are based on data from a single year, the partners are investigating additional validations with previous FWS-NRP survey estimates, and plan to continue re-evaluating these data relationships in future surveys. These findings extend previous work in partnership with the FWS where the eBird relative abundance product was validated as a way to define collision risk categories for eagles in relation to wind energy facilities (Ruiz-Gutierrez et al., 2021).

3.2. Migratory waterfowl monitoring

3.2.1. Validation – Sacramento National Wildlife Refuge Complex

Visual inspection of monthly abundance based on ground surveys and the eBird relative abundance product indicated high concordance across time and spatial scale for all waterfowl species in the FWS-SNWRC survey. Spearman rank analysis confirmed qualitative patterns for FWS-SNWRC surveys in California at the county and full extent scales, revealing strong positive, significant correlations between the FWS-SNWRC and eBird relative abundance datasets over time representing migration chronologies (mean $\rho = 0.81$; Supplementary Table S1) with the single exception of Mallard abundance within Butte County (Supplementary Table S1).

3.2.2. Validation – Illinois Natural History Surveys

INHS surveys were qualitatively similar to the eBird relative abundance product predictions throughout Fall-Winter, until week 25 (approximately 22 Feb.) where some INHS and eBird relative abundance product predictions began to diverge (e.g., Fig. 4). Across all INHS survey regions, correlations were on average weaker than those observed for the FWS-SNWRC dataset (mean $\rho = 0.72$; Supplementary Table S2). For individual species × region combinations, INHS and eBird relative abundance product predictions were moderately to strongly positively correlated, with the exception of Green-winged Teal in survey region 4 (Table Supplementary Table S2).

3.2.3. Predictions – Sacramento National Wildlife Refuge Complex

Because FWS-SNWRC survey data visually aligned with the eBird relative abundance product across the annual cycle, and had strong correlations, we built only Fall and Spring combined models to predict counts of waterfowl at the county and region scales. R^2 values were moderate to high across counties (mean $R^2 = 0.49$), and at the full extent scale (mean $R^2 = 0.63$), although some species had low model performance in certain regions (e.g., Gadwall, Mallard, and Ring-necked Duck abundance in Butte County; Fig. 5).

3.2.4. Predictions – Illinois Natural History Surveys

Because visual inspection highlighted substantial qualitative differences in INHS survey observations and eBird relative abundance product predictions during late Winter and into Spring months (e.g., Fig. 4), we built generalized linear models for the Fall season alone (i.e., when survey results were well-aligned), and for the entire Fall–Spring survey period, to quantify differences in model performance. With the exception of survey region 3, restricting our analysis to INHS Fall-only data substantially improved model performance (regions 1, 2, and 4 mean R^2 Fall-only model: 0.617, Fall-Spring: 0.339; Fig. 5). In region 3, R^2 decreased from 0.59 to 0.48 on average, among the Fall-Spring model to the Fall-only model, although the performance decrease varied substantially between species (Fig. 5).

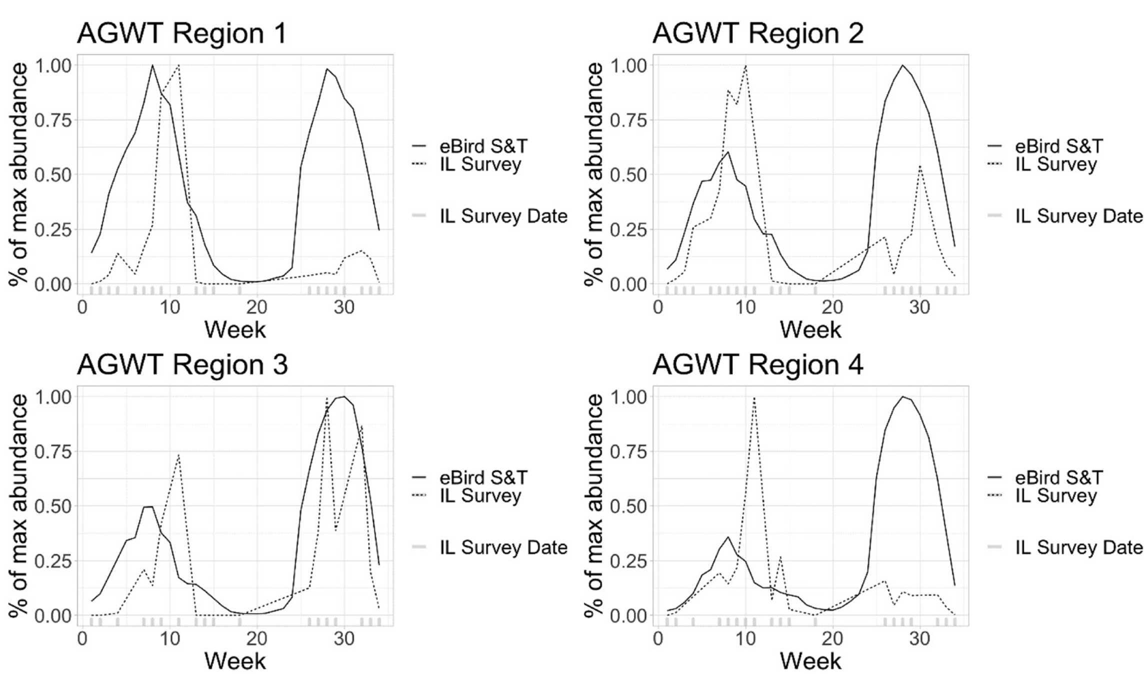

Fig. 4. Example weekly time-series of percent of maximum Green-winged teal abundance within 4 study regions based on data from the eBird relative abundance product developed by the Status and Trends team (solid line) and aerial surveys conducted by the Illinois Natural History Survey (dashed line). INHS surveys took place on weeks denoted by black tick marks on the x-axis.

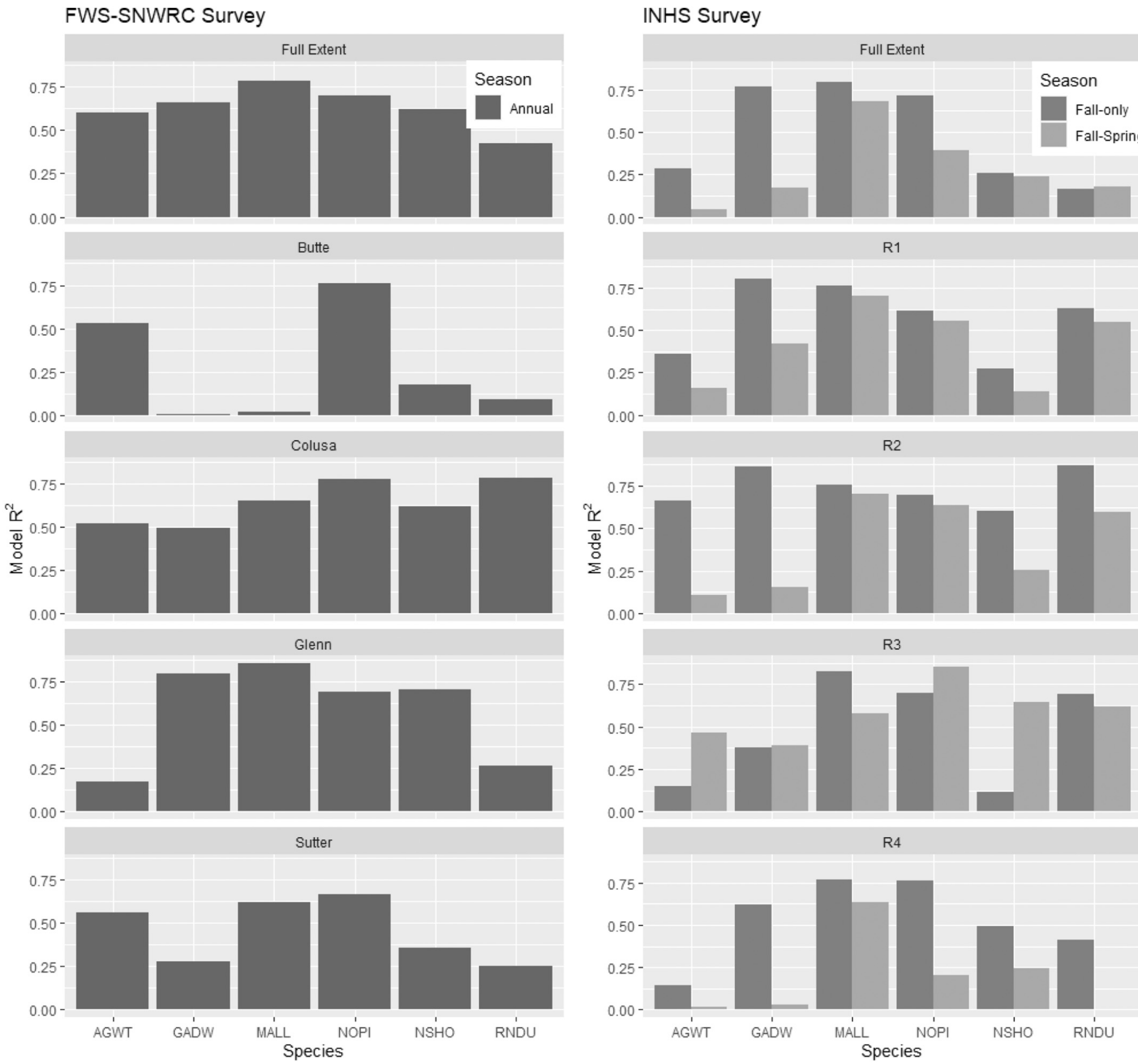

Fig. 5. R^2 values derived from models using eBird relative abundance as a predictor of waterfowl abundance. The eBird relative abundance estimates were developed by the eBird Status & Trends Project team, and observed waterfowl abundance were collected by professional biologists in the U.S. Fish and Wildlife Service – Sacramento National Wildlife Refuge Complex (left panel) and Illinois Natural History Survey (right panel). Models using surveys conducted by the Illinois Natural History Survey were run using data from both the Fall and Spring seasons (right panel, Fall-Spring: light gray), and data from the Fall season only (right panel, Fall-only: dark gray). AGWT = Green-winged Teal, GADW = Gadwall, MALL = Mallard, NOPI=Northern Pintail, NSHO=Northern Shoveler, RNDU = Ring-necked duck.

3.2.5. Management decision implications

The extent and frequency of waterfowl surveys in regions of key importance during the non-breeding period has declined over the past few decades amid safety concerns and shrinking budgets (Masto, 2019). Here, we demonstrated that CS data can produce migration chronologies and indices of waterfowl relative abundance that are reasonably similar to those from professional waterfowl surveys, for many species and sites included in our analysis. These results indicate that CS data have potential to be a valuable supplement to existing surveys and can in some cases stand in for missing data when professional surveys cannot be conducted (e.g., due to inclement weather, equipment failure, or agency closures; Howell et al., 2022). Furthermore, the temporal mismatches we observed in relative abundance between the two datasets have highlighted behavioral differences in waterfowl related to volume of water in channels. For example, when main river channels (where INHS surveys were conducted) were flooded, waterfowl moved into shallower off-channel wetlands where eBird users were more likely to observe them. Professional programs can use this information to decide whether they need to alter survey protocols to better match the ecology of the species, depending on the scale of interest for making inference (e.g., if inference is to be made at the specific waterway scale then survey protocol would not be altered, but if region-scale inference is needed then survey design should reflect space use patterns of focal species). More importantly, the eBird relative abundance products are seamless across the U.S., offering the opportunity for uniform cross-regional evaluations of migration chronologies and waterfowl distributions during autumn–winter. This would represent a major advancement towards the development of methodologically-consistent bioenergetic models and their application to coordinated conservation planning at inter-regional, flyway, or continental scales. However, important work remains to determine the utility of eBird relative abundance products for additional species (e.g., *Aythya* spp., the diving ducks, which may be more difficult to accurately detect) and in geographies or wetland types that citizen scientists do not regularly access (i.e., where raw CS data are sparse) yet independent datasets indicate are highly important for migrating and wintering waterfowl (e.g., Louisiana coastal marshes, Mississippi Alluvial Valley forested wetlands, Southern High Plains playa wetlands).

4. Discussion

Although biological monitoring data from CS projects have been exponentially increasing, their use in large scale conservation and management, and particularly in policymaking, has not kept pace with their availability. One of the major barriers to the uptake of CS in management decision-making and policy arenas is uncertainty about its scientific credibility both due to collection by largely non-professionals, and lack of traditional statistical sampling design in the largest CS projects. We presented example contexts where CS data products were validated against standard professional, targeted biological monitoring programs. Using three case studies that varied in their objectives, scope, and target species, we demonstrated that CS data can in some cases provide information directly useful and comparable to professionally run, targeted monitoring programs at the regional to national planning scales and offer additional benefits in terms of spatial and temporal resolution and extent. However, our case studies also demonstrated contexts where CS and standardized waterfowl surveys provide different, non-substitutable information, thus illustrating the importance of scale- and question-specific validation. By validating CS data against established scientific monitoring programs, agencies can begin considering pathways by which CS data could complement existing surveys and be incorporated into decision-making processes.

Identifying the cases where CS data can allow wildlife professionals to extend study coverage, reallocate resources, or supplement ongoing work has the potential to make resource use more efficient and effective. Efficient use of monetary resources is especially relevant given the current funding climate and the extent of conservation and management challenges. For example, funding for the U.S. Endangered Species Act has flatlined over the past decade without keeping pace with the number of species listed, resulting in ~88% of species with federal recovery plans receiving less funding than prescribed (Gerber, 2016). And while the U.S. Congress has allocated $5M per year to the Neotropical Migratory Bird Conservation Act, this amounts to only approximately $14,000 of funding per species. With 52% of budgets allocated in threatened species' recovery plans dedicated specifically to research and monitoring (Buxton et al., 2020), relatively low cost CS-enabled decision-making can be a boon to chronically under-resourced projects. Even resources for non-threatened and game species, largely funded through the Pittman-Robertson Federal Aid in Wildlife Restoration Act, can be stretched with CS for greater impact. For example, States could improve the efficiency of funding by relying on validated CS information for portions of species monitoring, and reapportioning funds towards active habitat restoration, land acquisition, or outreach efforts that typically benefit multiple wildlife species. While useful CS projects are not cost-free (e.g., the hosting institution or coordinating agencies may spend funds on recruitment and retention efforts, advertisement, and data storage), a substantial portion of the costs may be borne by agencies or institutes that are not the decision-makers themselves, and is less costly than running the same program but additionally paying volunteers for their time.

While few projects are currently large enough to support the type of data filtering that subsets only high-quality observations, they can broadly contribute to improvements in the quality and scope of evidence-based decision-making for conservation. For example, in addition to eBird, the eMammal camera trapping platform hosts millions of photos collected and interpreted by hundreds of volunteers globally (emammal.si.edu). In the UK, the British Trust for Ornithology has managed the quarterly Wetland Bird Survey since 1947, and in 2018, more than 3000 volunteers collected wetland bird data during 39,000 site visits (Frost et al., 2019). In these projects, both presence and absence data are recorded, and analysts can filter data entries based on quality for scientific purposes. Some of the largest platforms aggregating nature observations (e.g., Global Biodiversity Information Facility (GBIF), VertNet) or CS programs (e.g., iNaturalist) only host presence-only observations, and can therefore be relatively less valuable for scientific inference compared to complete checklists where identified species are not omitted when a survey or count was performed. However, many smaller-scale and newly initiated projects have been developed to collect presence-absence information of the highest quality for wildlife studies (e.g., UK Bat Conservation Trust's Sunset/Sunrise Survey; Everglades Invasive Reptile and Amphibian Monitoring Citizen Science Program), and have great potential to enhance localized, or species-specific management objectives.

By investigating multiple species and regions, we highlight variation in the ability of CS to explain targeted survey data geographically and by objective. For example, in our waterfowl case studies, we found strong evidence for CS information to be able to reproduce the migratory chronologies of professional surveys (i.e., consistently high rank correlations between time series of CS and professional surveys). However, CS information varied in its ability to replicate indices of waterfowl abundance across the season (e.g., INHS aerial surveys of Green-winged Teal in late Winter–Spring; Fig. 4). Specifically, we found that during late-Winter and Spring, when larger waterways within the INHS survey region are typically flooded, eBird participants' counts of individuals were concentrated in the shallower off-channel waterways where waterfowl had amassed in large numbers. During that time, INHS aerial surveys continued to be flown over the large waterways as dictated by survey protocols, resulting in low waterfowl counts in aerial surveys. If inference were to be made solely based on professional surveys we would have concluded that based on surveys of large waterways, the region had relatively low waterfowl abundance, whereas we would conclude that the region had high relative abundance during the same time period based on CS information where sampling locations shifted dynamically with accessibility and incidentally aligned with changes in species' space use. Similar systematic differences between survey protocols may also explain mismatches in expected abundance based on CS and FWS-SNWRC data, where model R^2 values were only moderate. Such differences in estimates of weekly relative abundance underscore the dynamics of species' space use and the importance of using survey protocols that align with a species' ecology. We found the two datasets non-substitutable, as systematic differences in survey design led to the relative abundance indices being poor predictors of each other for some species in some management units. With the information provided here, decision-makers may consider increasing or shifting professional survey effort, or incorporating the strengths of both datasets simultaneously. The eBird relative abundance product comprises weekly predictions of abundance, allowing for continuous estimation of population abundance across the annual cycle, and there are clearly benefits of joining complementary datasets (e.g., Robinson et al., 2020) to generate the best inference regarding population occurrence and abundance across the annual cycle. Formal data integration, whereby both datasets are analyzed jointly, rather than using one as a predictor for the other, may also be a fruitful avenue of future investigation, as much recent effort has gone in to developing these methods (Zipkin et al., 2019; Zulian et al., 2021). Interspecific and spatial variation in performance of eBird as a substitute for professional surveys underscores the initial need to test the datasets against each other in specific study systems to determine whether the data can stand in for each other, or whether the data represent complementary, semi-independent, information.

In our case studies, we highlighted some of the benefits that CS can afford professional management agencies. For example, by validating the eBird relative abundance product against aerial survey data for eagles, the FWS-NRP could now monitor trends in between updates to population size and estimates of allowable take. Although this temporal resolution is not needed in the FWS-NRP take limit framework, where the current level of temporal consistency is favored, shorter temporal gaps between population size updates would provide other programs with more precise monitoring of population trends. It is important to note, in our validation procedure with FWS-NRP that the eBird relative abundance product could not have been used in isolation of aerial survey estimates. Because the underlying units of both data sources did not directly match (i.e., mean number of occupied nesting territories, vs relative abundance of bald eagle individuals), a statistical 'adjustment factor' had to be identified to describe the relationship between the data. Further validation to determine the consistency of such 'adjustment factors' over time and space will be necessary to decide how to best incorporate eBird information into planning processes. Additionally, by validating the eBird relative abundance product, the FWS-NRP does not have to rely on State-run nest recording programs for observations of eagle nest sites in low density areas that have not been part of the aerial survey design. State-run nest observations have been irregularly maintained over time, and their data collected with varying effort as the status of the bald eagle improved and State resources were directed to higher priorities (U.S. Fish and Wildlife Service 2016b). Based on work from this collaboration, the FWS-NRP is planning to incorporate eBird-based results to directly inform revisions to policy regulations regarding the incidental take of bald eagles and eagle nests (U.S. Fish and Wildlife Service 2016a, 2020a).

Although incorporating CS into decision-making frameworks has substantial potential benefits, there are tangible barriers for the validation and use of this information. The one most obvious barrier is that not all CS projects make their data publicly available or easily accessible. However, the largest citizen science projects are housed within centralized institutions such as eBird, at the Cornell Lab of Ornithology, and GBIF, at the Natural History Museum of Denmark, which actively facilitate broad CS data use, and access is becoming increasingly straightforward. Working in cross-agency teams of data generators, data analysts, and data users enabled an efficient, targeted investigation of the usefulness of CS in current management-relevant scenarios.

The results of our case studies demonstrate how semi-structured CS can represent a powerful evidence base from which to inform certain conservation and management decisions, and frame policy recommendations. Broad investigations using transparent, reproducible, and open practices that include end-users from start to finish can establish CS data as a trusted and reliable source of information from which to base wildlife management decisions. The continued inclusion of CS data in policy frameworks also requires coordination between agencies and CS projects to ensure that data are available in time to meet the regulatory schedules imposed on public agencies by legal precedents. With its low cost, high resolution information, and open-source availability, a wide range of management agencies and policy influencers, globally, may benefit from incorporating semi-structured CS into the decision-making process.

CRediT authorship contribution statement

Erica F. Stuber: Conceptualization, Methodology, Writing-Original draft preparation, Reviewing and editing,
Orin J. Robinson: Conceptualization, Methodology, Data curation, Writing-Reviewing and editing, Visualization
Emily R. Bjerre: Data curation, Project administration, Writing-Reviewing and editing,
Mark C. Otto: Data curation, Writing-Reviewing and editing,
Brian A. Millsap: Project administration, Supervision, Writing-Reviewing and editing,
Guthrie S. Zimmerman: Writing-Reviewing and editing,
Michael G. Brasher: Conceptualization, Project administration, Writing-Reviewing and editing,
Kevin M. Ringelman: Conceptualization, Project administration, Writing-Reviewing and editing,
Auriel M.V. Fournier: Data curation, Project administration, Writing-Reviewing and editing,
Aaron Yetter: Data curation, Writing-Reviewing and editing
Jennifer E. Isola: Data curation, Supervision, Writing-Reviewing and editing, Visualization
Viviana Ruiz-Gutierrez: Conceptualization, Supervision, Writing-Reviewing and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors thank all eBird participants for their contributions, and Daniel Fink and the entire eBird Status & Trends team for their support. The authors gratefully acknowledge funding from the U.S. Fish and Wildlife Service, the Federal Aid in Wildlife Restoration Program (INHS surveys) and the U.S. Geological Survey (in-kind). The funding sources were not involved in conducting this research or in preparation of this manuscript. Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government. The findings and conclusions in this article are those of the authors and do not necessarily represent the views of the U.S. Fish and Wildlife Service.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2022.109556.

References

Anderson, M.G., Padding, P.I., 2015. The north american approach to waterfowl management: synergy of hunting and habitat conservation. Int. J. Environ. Stud. 72, 810–829.

Bonney, R., Cooper, C.B., Dickinson, J., Kelling, S., Phillips, T., Rosenberg, K.V., Shirk, J. J.B., 2009. Citizen science: a developing tool for expanding science knowledge and scientific literacy. Bioscience 59, 977–984.

Buxton, R.T., Avery-Gomm, S., Lin, H.-Y., Smith, P.A., Cooke, S.J., Bennett, J.R.J.N.C., 2020. Half of resources in threatened species conservation plans are allocated to research and monitoring. Nat. Commun. 11, 1–8.

Cooper, C.B., Hawn, C.L., Larson, L.R., Parrish, J.K., Bowser, G., Cavalier, D., Dunn, R.R., Haklay, M.M., Gupta, K.K., Johnson, V.A., Katti, M., 2021. Inclusion in citizen science: the conundrum of rebranding. Science 372 (6549), 1386–1388.

Fink, D., Auer, T., Johnston, A., Strimas-Mackey, M., Robinson, O., Ligocki, S., Hochachka, W., Wood, C., Davies, I., Iliff, M., Seitz, L., 2020a. eBird status and trends, data version: 2019; released: 2020. Cornell Lab of Ornithology, Ithaca, New York. https://doi.org/10.2173/ebirdst.2019.

Fink, D., Auer, T., Johnston, A., Ruiz-Gutierrez, V., Hochachka, W.M., Kelling, S., 2020b. Modeling avian full annual cycle distribution and population trends with citizen science data. Ecol. Appl. 30 (3), e02056.

Fleming, K.K., Brasher, M., Humburg, D., Petrie, M., Soulliere, G., 2017. Derivation of regional, non-breeding duck population abundance objectives to inform conservation planning. In: North American Waterfowl Management Plan Science Support Team Technical Report 2017-01.

Fleming, K.K., Brasher, M., Humburg, D., Petrie, M., Soulliere, G., 2019. Derivation of regional, non-breeding duck population abundance objectives to inform conservation planning. In: North American Waterfowl Management Plan Science Support Team Technical Report 2019 Revision.

Station, Forbes Biological, 2020. Aerial Waterfowl Surveys of the Illinois and Mississippi Rivers. Dataset collected by Forbes Biological Station Staff, Illinois Natural History Survey, Prairie Research Institute, University of Illinois Urbana-Champaign, Havana, IL.

Frost, T., Austin, G., Calbrade, N., Mellan, H., Hearn, R., Robinson, A., Stroud, D., Wotton, S., Balmer, D., 2019. Waterbirds in the UK 2017/18: The Wetland Bird Survey. BTO/RSPB/JNCC, Thetford.

Gerber, L.R., 2016. Conservation triage or injurious neglect in endangered species recovery. Proc. Natl. Acad. Sci. 113, 3563–3566.
Howell, P., Devers, P., Robinson, O., Royle, J.A., 2022. Leveraging community science data for population assessments during a pandemic. Ecological Applications, e2529.
Johnston, A., Hochachka, W.M., Strimas-Mackey, M., Gutierrez, V.R., Robinson, O.J., Miller, E.T., Auer, T., Kelling, S.T., Fink, D.J.B., 2022. Analytical guidelines to increase the value of community science data: an example using eBird data to estimate species distributions. Diversity and Distributions 27 (7), 1265–1277.
Kelling, S., Johnston, A., Bonn, A., Fink, D., Ruiz-Gutierrez, V., Bonney, R., Fernandez, M., Hochachka, W.M., Julliard, R., Kraemer, R.J.B., 2019. Using semistructured surveys to improve citizen science data for monitoring biodiversity. Bioscience 69, 170–179.
Masto, N.M., 2019. Evaluation of aerial surveys to monitor fall-winter waterbird populations in South Carolina. Clemson University, South Carolina, USA, Thesis.
Nichols, J.D., Williams, B.K., 2006. Monitoring for conservation. Trends Ecol. Evol. 21, 668–673.
Prudic, K.L., McFarland, K.P., Oliver, J.C., Hutchinson, R.A., Long, E.C., Kerr, J.T., Larrivée, M.J.I., 2017. eButterfly: leveraging massive online citizen science for butterfly conservation. Insects 8, 53.
Ringelman, K.M., Williams, C.K., Castelli, P.M., Sieges, M.L., Longenecker, R.A., Nichols, T.C., Earsom, S.D., 2018. Estimating waterfowl carrying capacity at local scales: a case study from Edwin B. Forsythe National Wildlife Refuge, New Jersey. J. Fish Wildl. Manag. 9, 106–116.
Robinson, O.J., Ruiz-Gutierrez, V., Reynolds, M.D., Golet, G.H., Strimas-Mackey, M., Fink, D., 2020. Integrating citizen science data with expert surveys increases accuracy and spatial extent of species distribution models. Divers. Distrib. 26, 976–986.
Ruiz-Gutierrez, V., Bjerre, E., Otto, M., Zimmerman, G., Millsap, B., Fink, D., Stuber, E.F., Strimas-Mackey, M.E., Robinson, O.J., 2021. A pathway for citizen-science data to inform policy: a case study using eBird data for defining low-risk collision areas for wind energy development. J. Appl. Ecol. 58 (6), 1104–1111.
Shirk, J.L., Ballard, H.L., Wilderman, C.C., Phillips, T., Wiggins, A., Jordan, R., McCallie, E., Minarchek, M., Lewenstein, B.V., Krasny, M.E., Bonney, R., 2012. Public participation in scientific research: a framework for deliberate design. Ecol. Soc. 17 (2).
Stafford, J.D., Horath, M.M., Yetter, A.P., Hine, C.S., Havera, S.P., 2007. Wetland use by mallards during spring and fall in the Illinois and Central Mississippi River valleys. Waterbirds 30 (3), 394–402.
U.S. Fish and Wildlife Service, 2009. Post-delisting Monitoring Plan for the Bald Eagle (Haliaeetus leucocephalus) in the Contiguous United States. Divisions of Endangered Species and Migratory Birds and State Programs, Midwest Regional Office, Twin Cities, Minnesota.
U.S. Fish and Wildlife Service, 2016. In: Eagle Permits; Revisions to Regulations for Eagle Incidental Take and Take of Eagle Nests. Federal Register, pp. 91494–91554.
U.S. Fish and Wildlife Service, 2019. Sacramento National Wildlife Refuge Complex (Draft) protocol for the inventory and monitoring of wildlife populations. Sacramento NWR, Willows, CA.
U.S. Fish and Wildlife Service, 2020. Final Report: Bald Eagle Population Size: 2020 Update. U.S. Fish and Wildlife Service, Division of Migratory Bird Management, Washington, D.C. U.S.A.
U.S. Fish and Wildlife Service, 2020. In: NWR, S. (Ed.), Sacramento National Wildlife Refuge Complex Regular Wildlife Surveys: 2001-2018. Unpublished raw data, Willows, CA.
U.S. Fish and Wildlife Service, Division of Migratory Bird Management, 2016. Bald and golden eagles: population demographics and estimation of sustainable take in the United States, 2016 update.
Yoccoz, N.G., Nichols, J.D., Boulinier, T., 2001. Monitoring of biological diversity in space and time. Trends Ecol. Evol. 16, 446–453.
Zimmerman, G.S., Millsap, B.A., Abadi, F., Gedir, J.V., Kendall, W.L., Sauer, J.R., 2022. Estimating allowable take for an increasing bald eagle population in the US. J. Wildl. Manag. 86, e22158 https://doi.org/10.1002/jwmg.22158.
Zipkin, E.F., Inouye, B.D., Beissinger, S.R., 2019. Innovations in data integration for modeling populations. Ecology 100 (6), e02713. https://doi.org/10.1002/ecy.2713.
Zulian, V., Miller, D.A., Ferraz, G., 2021. Integrating citizen-science and planned-survey data improves species distribution estimates. Divers. Distrib. 27 (12), 2498–2509.