Quantifying the Value of Community Science Data for Conservation Decision-making

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Data Availability

Data for this project are available at DOI 10.17605/OSF.IO/E536U.

Note that the shapefiles for private properties have been removed from this version to protect the privacy of the landowners involved in this project.

Code Availability

Code for the analyses in this project are available at DOI 10.17605/OSF.IO/E536U.

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Abstract

Monitoring biodiversity can be critical for informing effective conservation strategies, but can also deplete the resources available for management actions. Freely-available community science data may help alleviate this issue, but only if data quality is sufficient to inform the best decisions. Our objective was to quantify the predicted outcomes of prioritizing conservation action based on regional community science compared to using targeted professional monitoring data. Using data from the BirdReturns program in the Central Valley of California as a case study, we prioritized management units for conservation action based on the predicted probability of detecting seven shorebird species. Crowd-sourced data performed better than professional data even before accounting for the cost of professional monitoring, and substantially better when monitoring costs were explicitly considered. Thus, conservation action based on freely-available community science data could theoretically result in better biodiversity outcomes than paying for targeted professional monitoring.

Keywords: citizen science, conservation, agriculture, shorebirds, BirdReturns, Central Valley, habitat enhancement, site selection, eBird

Introduction

Improving the evidence base for conservation decisions is the impetus for many biodiversity monitoring programs. Increasing our knowledge of a system can lead to better conservation outcomes (Runting, Wilson, and Rhodes 2013), and thus presents a worthwhile investment. However, some studies suggest that collecting additional information may not be beneficial for decision making (Moore and McCarthy 2010), and delaying action in favour of collecting more information can be detrimental (Martin et al. 2012). Despite half of conservation budgets allocated for threatened species recovery being spent on research and monitoring (Buxton et al. 2020), the trade-offs between spending on information gathering versus action remain poorly understood.

Extensive biodiversity data exist that can potentially be used to inform conservation decisions (e.g., GBIF (GBIF: The Global Biodiversity Information Facility 2022); eBird (Sullivan et al. 2014); iNaturalist (Callaghan et al. 2020)). For instance, data from community science programs (also commonly known as “citizen science”) are often readily available and freely accessible (Binley et al. 2023). Since these data are gathered by the public, they have extensive spatial coverage and are less costly than hiring professionals to collect data (Heigl et al. 2017; Theobald et al. 2015). However, there are concerns that less structured protocols and greater variation in observer skill may yield less accurate results than professional monitoring (Binley and Bennett 2023; Munson et al. 2010). Furthermore, since many of these programs are opportunistic, the capacity for targeting data collection precisely where it is needed is more limited. Professional monitoring, while more costly and limited in spatial scope, can be directed to areas that will yield the most useful information for decision making, including areas that have limited access to community scientists. Although previous studies have compared species’ diversity and abundance estimates derived from professional monitoring protocols and community science programs (e.g., (Kamp et al. 2016; Munson et al. 2010; Walker and Taylor 2017), it is not clear whether discrepancies between the different approaches would, in turn, result in different conservation decisions (Grantham et al. 2008; Polasky and Solow 2001).

Here we investigate whether untargeted, crowd-sourced community science data is of sufficient quality to inform conservation prioritizations, comparing them to professional monitoring efforts targeted on privately-owned properties enrolled in a conservation program. Furthermore, we assess whether the cost savings afforded by using the freely available community science data could aid in redistributing resources from monitoring to action, potentially leading to better outcomes for biodiversity. To achieve this, we used data from a dynamic conservation program run by the Nature Conservancy (TNC) in central California as a case study. We generated theoretical conservation plans (henceforth, prioritizations) that selected rice farms to enroll in the conservation program by minimizing costs and maximizing the predicted number of detections of seven shorebird species on enrolled properties based on species distribution data derived from (i) community science (from the eBird community science project), (ii) targeted professional monitoring data only (collected by TNC), and (iii) both community science and professional data integrated. Community science data were available for the region, but rarely on the rice fields that were candidates for enrollment in the program. Professional monitoring was conducted on the private properties to fill this habitat coverage gap, as well as to monitor habitat conditions, address research questions and assess landowner compliance. While the professional monitoring for this program served multiple purposes, our analysis focuses solely on the biodiversity information content to assess its relative utility for prioritizing conservation action. In addition to the costs associated with implementing conservation action, which in this case involves enrolling properties in the conservation program, our prioritizations accounted for monitoring costs. Specifically, prioritizations based on the professional data or the integrated community science and professional dataset had their total budget reduced by the cost of monitoring. Since the community science dataset is open and freely available, prioritizations based on this dataset were assumed to have zero field monitoring costs. After generating the prioritizations, we assessed the performance of each dataset based on the number of bird detections captured across all properties selected in our theoretical prioritization.

Materials and Methods

The BirdReturns program is a dynamic conservation project by The Nature Conservancy (TNC) in central California that aims to provide temporary habitat for migratory shorebirds (Reynolds et al. 2017). Over 90% of California's native wetlands have been lost to agricultural expansion (Dahl 1990; Frayer, Peters, and Pywell 1989), creating a potentially hostile environment for migratory birds that rely on them to rest and refuel. However, by flooding harvested rice fields for a few weeks during spring and fall migration, conservation practitioners can create "pop-up wetlands" that meet the needs of species as they pass through, temporarily restoring high quality habitat for their use when and where they need it (Golet et al. 2018, 2022). Any costs associated with habitat creation on the farms are offset by a reverse auction system, whereby farmers bid the amount of compensation they would require to flood their fields for a set period of time. TNC uses eBird community science data, data collected from previously enrolled fields, and remotely-sensed land cover data to rank the shorebird habitat value of properties being considered for enrollment in the program (Reynolds et al. 2017). This information is used in conjunction with bid prices submitted through a reverse auction to select enrollments for the program. Professional monitoring is then used to assess habitat conditions and patterns of bird use in a subset of enrolled and (in some cases) unenrolled fields during program implementation. The purpose of this monitoring is to evaluate program effectiveness and better understand how local and landscape-scale factors affect bird response for refining requirements of the program and improve the analytical models (e.g., Conlisk et al. 2022) used to inform bid selection in future auctions. In addition, professional monitoring is done to assess compliance so that landowners can be instructed to take corrective actions when target habitat requirements are not being met. Thus, both community science and professional monitoring data are used in the true implementation of the BirdReturns program. For more information on the BirdReturns program, see (Golet et al. 2018; Reynolds et al. 2017).

Given that both community science and professional datasets are available for the same species and locations, this presents a unique opportunity to compare the relative value of each dataset to inform the prioritization of conservation action, in this case enrollment of properties in the BirdReturns program. We emphasize that our analysis focuses on the trade-offs between monitoring costs and information content, but does not account for the other aforementioned purposes of professional monitoring. Models of predicted probability of detection for each species were developed by Robinson et al. (2020), providing a uniform metric for prioritization using each dataset, as well as an integrated model that performs better than using either dataset alone (see details under "Prioritizations"). The integrated model predictions can therefore serve as the benchmark of the best available information (Robinson et al. 2020; Runting et al. 2013) with which we can evaluate the value of decisions based on each dataset individually. Correcting for the sensitivity and specificity of the integrated model (Robinson et al. 2020), we can use the estimates as our best knowledge of where species are truly detected while accounting for uncertainty in these estimates. The size and location of 207 properties that submitted reverse auction bids were used in this analysis. Detailed information on the cost of monitoring and action is available from TNC (Appendix A). Thus, this case study represents a realistic applied conservation scenario, with real biodiversity data and operational costs.

Data Collection Protocols

Surveys conducted by TNC consisted of 8,192 point counts conducted between February 1 and May 31, 2014-2017. All birds within a 200m radius semicircle were recorded. Observers searched for birds for at least two minutes, but continued until all visible individuals in the semi-circle were recorded. Information was collected on the identity of the observer, the duration of the count, and the date, as well as habitat conditions such as water depth, vegetation cover and weather. Point count locations were randomly assigned to both treatment and control fields enrolled in the BirdReturns program. Treatment fields are those that were enrolled in the program and therefore adhered to program requirements regarding flood depth and minimal standing vegetation. Control fields are those that were not enrolled in the program and therefore did not follow these requirements, though many were still flooded. For more details, see (Golet et al. 2018).

eBird is a semi-structured community science program that allows participants of any skill level to submit checklists of species observed at any time or location (Sullivan et al. 2014). Although eBird observations are opportunistic (i.e., not following a set monitoring protocol), users must submit information such as time of day, time spent searching, distance travelled, and whether the checklist represents a complete account of all species that were seen and identified in the field. These covariate data can then be used to control for additional sources of variation introduced by the opportunistic method of recording data (Johnston et al. 2021). In this study, eBird checklists were filtered to only include observations collected during the same period of the year as TNC surveys and limited to the extent of the California Central Valley. This is approximately the extent of TNC surveys, but not limited to the fields enrolled in the program. Checklists were further filtered to include only complete checklists, and stationary counts or travelling counts that cover less than 300m, resulting in 12,891 checklists used in the analysis (Robinson et al. 2020). Although more eBird checklists were used than professional surveys, we see this as a realistic benefit of using crowd-sourced data for conservation. Furthermore, Robinson et al. (2020) found limited improvement in model performance when the eBird dataset was augmented with simulated data by the number of TNC point counts (n = 8,192), suggesting that sample size did not play a substantial role. Since very few eBird checklists were collected on the properties, yet the performance of each model was limited to how well they could predict species detections on these properties, the quantity of eBird checklists likely provided no discernible advantage over the professional surveys in our analysis.

Species

We prioritized management units for conservation action based on the modeled probability of detection for seven migratory shorebird species during spring migration: American Avocet (*Recurvirostra americana*), Dunlin (*Calidris alpina*), Yellowlegs (*Tringa melanoleuca* and *Tringa flavipes*), Least sandpiper (*Calidris minutilla*), Long-billed Curlew (*Numenius americanus*), Dowitcher (*Limnodromus scolopaceus* and *Limnodromus griseus*) and Western Sandpiper (*Calidris mauri*). Greater and Lesser Yellowlegs were grouped as one species for analysis ("Yellowlegs"), as were Short-billed and Long-billed Dowitchers ("Dowitchers"), due to the difficulty distinguishing between these species at distance in the field, both for professional and amateur observers (Golet et al. 2018).

Monitoring and Action Costs

Monitoring costs were based on the real operational costs incurred by TNC during the BirdReturns program between 2014 and 2015 for spring monitoring only (Golet et al. 2018; Reynolds et al. 2017), to match the data used by (Robinson et al. 2020), totalling $121,622 USD (Appendix A). This includes the cost of supplies, truck rentals, and field technicians to conduct surveys. Although there are costs associated with the time required to process and analyze eBird data, these were assumed to be approximately equivalent to data processing requirements for TNC data. Costs associated with data analysis for both datasets were therefore excluded from this study. We did not include costs associated with the implementation of the eBird program as these are external to the costs incurred by the conservation organization. That is, we assume that the eBird data will be available regardless of whether we choose to use them for conservation planning.

Reverse auction bids were based on the 2014 pilot season of the BirdReturns program. We simulated bid values for each property using the average and standard deviation for accepted bids only, drawing from a normal distribution. We therefore assume here that all 207 farms in our study made acceptable bids and would be considered for the program. We simulated bid values based on the real data, rather than using the real bid values attached to each property, to capture the real characteristics of the bids while ensuring these results remain generalizable across other contexts and regions. As the farms are real properties, they vary in size, and bid values are based on a price per unit of area. The total cost of enrolling a property in the program through the reverse auction process will be referred to as the Property Cost (Table 1).

Table 1. Glossary of important terms used throughout this study and how they are defined for our purposes.

Term	Definition
Property Cost	Total cost of enrolling a farm in the program, calculated as the reverse auction bid in price per unit area multiplied by the area of the property.

Conservation Action	In this study, conservation action involves enrolling a property in the BirdReturns program. The property owner's reverse auction bid is accepted and their field is flooded to provide "pop-up" wetland habitat.
Predicted Species Detections	For each property, this is the sum of modeled probabilities of detecting a species across all cells. Prioritizations are based on maximizing the Predicted Species Detections estimated by each model for each species.
Expected Species Detections	The probability that a species is detected given the binary predictions of the integrated model for each cell, accounting for the prevalence of the species and the probability of false positives and false negatives using Bayes Theorem (see equations 1 and 2). Cell values are then summed for each property. Note that this does not correct for the sensitivity and specificity of surveys themselves (which are unknown), because we assume that managers will only consider a "success" to be a detected occurrence. The 100 iterations of the test and training datasets used to calculate sensitivity and specificity result in 100 Expected Species Detection values for each

	property. The integrated model (and therefore Expected Species Detections) represents the best available information on species detection according to Robinson et al. (2020).
Expected Detections Prioritized	The sum of Expected Species Detections across all farms selected in prioritizations for each species, at each budget, based on each model. There are 100 values for each prioritization, based on the 100 Expected Species Detection values for each property.

<u>Prioritizations</u>

For each of the seven study species, (Robinson et al. 2020) built random forest models predicting the probability that an expert observer would detect the species during a standardized survey, using observation effort, observer skill, land cover predictors, and either (i) eBird data only, (ii) TNC data only, or (iii) an integrated TNC and eBird dataset. Predictions were made across the Central Valley in California at a 500 m × 500 m resolution, and models were selected based on outputs that maximized accuracy based on Cohen's Kappa, Brier score, and Mean Standard Error. For more details on the models, see Robinson et al. (2020). We overlaid the model predictions onto the farms and, for each farm and each species, computed the sum of the species' probability values associated with the cells that overlapped with the farm. For example, a 0.75 km^2 property (i.e., three 500 m × 500 m cells) with predicted probabilities of detection of 0.5, 0.6 and 0.6 in each cell would have a total value of 1.7. Henceforth we will refer to these summed probability values as the Predicted Species Detections on the property (Table 1). Analyses were completed using the *R* statistical computing environment (R Core Team 2020) and *tidyverse* family of packages (Wickham et al. 2019). Spatial data processing was performed using the *raster* R package (Hijmans 2020).

Here, we assume that conservation success is associated with the number of detected species occurrences on management units selected in our prioritizations. We prioritized properties for enrollment in the BirdReturns program based on the predicted probability of detections (Predicted Species Detections) as estimated using community science data (the eBird model), professional monitoring data (the TNC model) and the best available model (the integrated model; Figure 1). To achieve this, we used the *prioritizr* R package (Hanson et al. 2022) to generate single species prioritizations under 30 different budgets ranging from \$0 to \$1,500,000 USD (with \$50,000 USD increments). For each budget, we used a minimum shortfall objective, which aims to find the set of management units that minimizes the shortfall for conservation targets (see (Jung et al. 2021) for details). In this case, we set targets to 100% representation for each species, so that prioritizations aim to maximize the number of detections on selected management units. We selected management units that maximized the Predicted Species Detections for each species while minimizing Property Costs, selecting as many management units as possible within the budgetary constraints. To account for monitoring costs, we subtracted \$121,622 USD from the available budget for prioritizations based on the professional data model (Appendix A). The result was a selection of properties to enroll for each species and at each budget, depending on the Property Cost and where each respective model predicted the highest probabilities of detection for each species (Predicted Species Detections).

Evaluation of Prioritizations

We used the integrated model predictions as a benchmark (in other words, an imperfect gold standard) to assess the performance of the prioritizations. This is because the integrated models had better performance than the eBird and TNC models. To account for the fact that the integrated models do not have perfect predictive ability, the integrated models' predictions were corrected before using them to evaluate the prioritizations. By correcting the integrated models' predictions, we could evaluate how well the prioritizations generated using the eBird models, TNC models, and integrated models covered each of the species, whilst accounting for model uncertainty.

We used performance statistics from Robinson et al. (2020) to correct the integrated models' predictions. Briefly, Robinson et al. (2020) employed a repeat sampling process to produce 100 estimates of the sensitivity (true positive rate) and specificity (true negative rate) for each species' model. For each of these 100 estimates, we used them to identify a detection threshold to convert a given integrated models' predictions from a probability of detection to a binary (detected or not detected) value. Specifically, the detection threshold was selected by maximizing Cohen's Kappa, a measure of the agreement between predictions and actual survey outcomes from a test set that accounts for the probability of random agreement. After identifying these detection thresholds, we then used them to produce 100 sets of binary predictions indicating whether the species was likely to be detected in each cell. Thus, for each species, we produced 100 sets of binary predictions, and for each set of binary predictions, we had a sensitivity and a specificity statistic to characterize uncertainty in the given set binary predictions.

We used Bayes theorem to produce a set of 100 corrected integrated model predictions for each species. We used species prevalence as the prior probability of a species being detected in each cell, calculated as the proportion of field sites where the species was detected on professional surveys (Appendix B; Table S1). By applying Bayes theorem, our methodology accounts for model uncertainty based on the sensitivity and specificity of the integrated models. Specifically, if a given species was predicted to be detected in a cell under a given set of binary predictions, we used the following equation:

$$P(detected \mid predicted\ detected) = \frac{sensitivity * prevalence}{sensitivity * prevalence + (1 - specificity)(1 - prevalence)}$$

[eqn. 1]

Alternatively, if the species was predicted to be not detected in the given cell, then we used the following equation instead:

$$P(detected \mid predicted\ not\ detected) = \frac{(1 - sensitivity) * prevalence}{(1 - sensitivity) * prevalence + specificity * (1 - prevalence)}$$

[eqn. 2]

We used the corrected integrated model predictions to evaluate the prioritizations. Because the corrected integrated model predictions were produced for each cell and the prioritizations were generated using properties, we needed to spatially aggregate these predictions to the property level so they could be used to evaluate the prioritizations. As such, for each of the 100 sets of corrected integrated model predictions for each species, we overlaid a given set of corrected model predictions with the property boundaries and calculated the sum of the predictions (probability values) within each property. Thus, for each property and each species, we produced 100 estimates of the expected number of cells inside the property that are likely to contain the given species (termed Expected Species Detections, see Table 1). The Expected Detections Prioritized (Table 1) for a given model and budget is equal to the sum of Expected Species Detections across all properties that were selected for Conservation Action in the prioritization.

Relative value of community science data

At each budget, we compared the total Expected Detections Prioritized based on each of the three model predictions and at each budget. For each of the 100 iterations *i*, we calculated the difference in the Expected Detections Prioritized between community science prioritizations ($V(P_c)$) and professional monitoring prioritizations ($V(P_p)$):

$$\Delta\, Expected\ Detections\ Prioritized = V(P_c)_i - V(P_p)_i$$

For each repetition, we also compared the value of prioritizations based on the integrated model ($V(P_g)$), our benchmark of the best available information, to those based on community science data to quantify the difference between decisions based on community science data and the best available information:

$$\Delta\, Expected\ Detections\ Prioritized = V(P_g)_i - V(P_c)_i$$

For each comparison, we calculated the mean difference in performance between the two prioritizations, and the lower and upper limits of the shortest range within which 90% of the values occurred (i.e., 90% high density interval (HDI), represented using square brackets in the results).

To assess how much the monitoring costs influenced our results, we conducted two supplementary analyses: 1) we conducted the community science – professional monitoring comparison without adding monitoring costs to the professionally-collected data, and 2) we added the monitoring costs to the integrated – community science comparison, to account for the realistic costs of having the best available information.

Quantifying the Financial Value of Community Science Data

During the spring enrollment period for the BirdReturns program in 2014, TNC spent approximately $400,000 USD on monitoring and the reverse auction. To quantify the financial value of eBird data for prioritizing action at this budget, we assessed the difference in the budget required to achieve the same number of Expected Species Detections if Conservation Action were based on professional monitoring data instead. For this analysis, we ignore the other purposes of professional monitoring and focus solely on biodiversity information provided. Starting at a budget of $400,000 USD, we prioritized properties using the estimates of detection from the professional data model at budgets increasing by $10,000 USD increments, until the Expected Detections Prioritized based on professional data alone was approximately equal to the Expected Detections Prioritized using eBird (i.e., until the 90% HDI of the differences overlapped zero).

Results

In our case study, we found that using community science data resulted in the best prioritizations across budgets and species when accounting for the cost of professional monitoring. When the monitoring cost of $121,622 USD was applied to the overall budget, prioritizations conducted using professionally-collected data had no expected detections prioritized, which we define as the expected number of bird detections in prioritized properties (see Table 1 for details), for budgets below $150,000 USD. This is because most or all of lower budgets were consumed by monitoring costs. Unsurprisingly, the difference in performance was most pronounced at lower budgets, declining until the budget exceeded the cost of enrolling all properties in the program ($1,001,915; Figure 1, Appendix B Figure S1). This was consistent across species, and the value of prioritizations based on professional data never met or exceeded the value of prioritizations using eBird data until this point. The greatest mean difference in performance was seen for Dowitcher (*Limnodromus scolopaceus* and *Limnodromus griseus*) at a budget of $150,000 USD: prioritizations using eBird data resulted in a 117.28% [99.35,125.97] increase in number of expected detections prioritized across selected farms. The smallest mean difference at this budget was seen for Western Sandpiper (*Calidris mauri*), where we still found a 105.08% [85.67,118.51] increase in coverage. Even when monitoring costs were not included in the professional monitoring prioritizations, prioritizations using community science data performed equally well across all species and budgets (Appendix B; Figure S2-S3). The expected detections prioritized using community science data even exceeded those based on the professionally-collected data for some species at certain budgets, but never more than an average of 8.08% [-0.45, 15.26], and the 90% HDI usually overlapped zero. That is, even before the cost of collecting the professional data were considered, the information content of both datasets for making decisions was approximately equal.

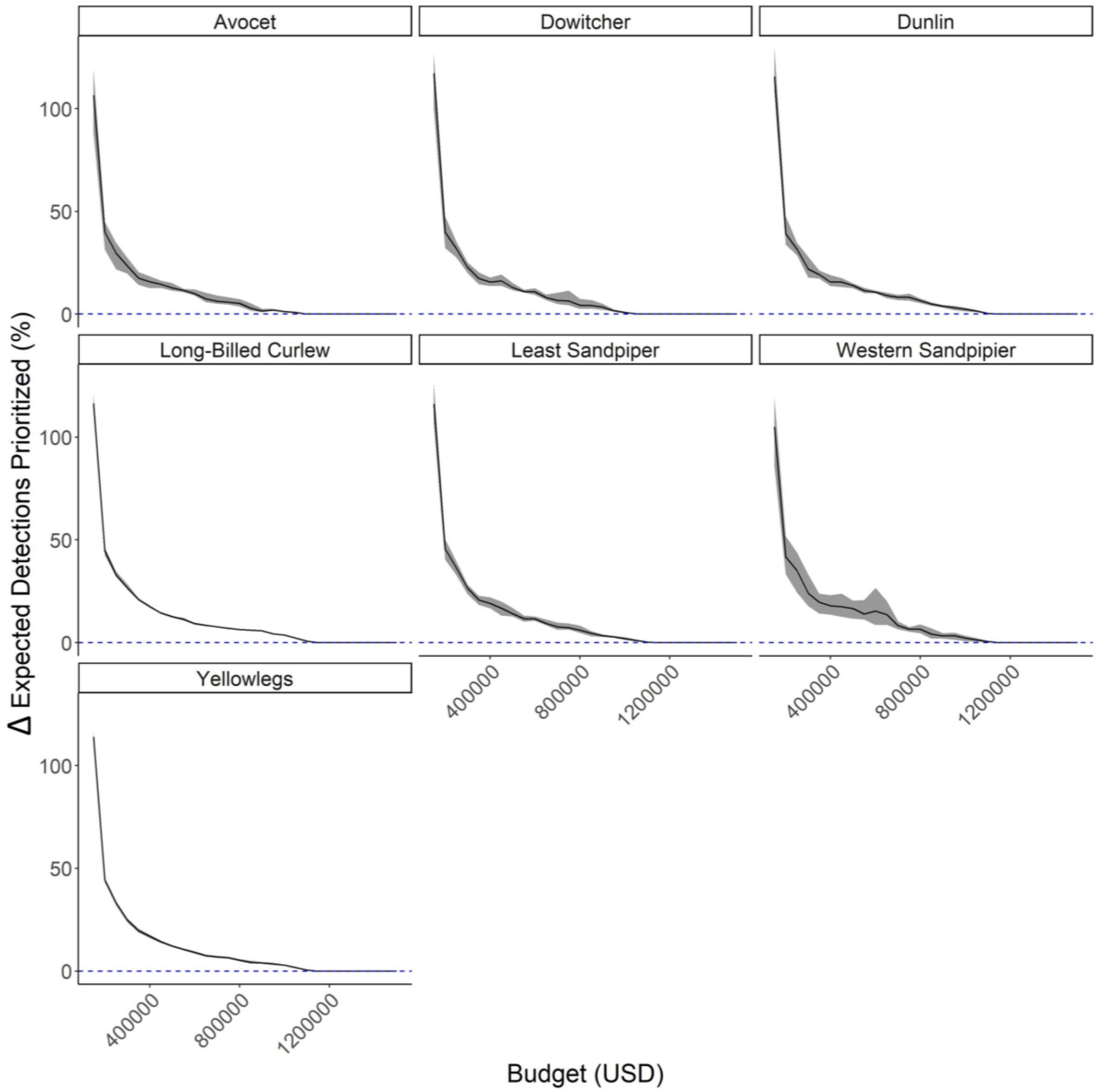

Figure 1. Percent improvement in expected detections prioritized across a range of budgets when basing prioritizations on community science data compared to professional data collected by on-site field technicians, accounting for the cost of collecting professional field data. Solid lines represent the mean difference in the expected detections prioritized between the two prioritizations, and shaded regions represent the 90% high density interval of these contrasts. Positive values indicate that prioritizations

based on community science performed better, while negative values indicate that prioritizations based on professional data performed better.

Prioritizations based on the integrated model, which represents the best available information on this system according to (Robinson et al. 2020), performed slightly better than those using community science data alone (Figure 2, Appendix B Figure S4). The greatest difference in performance was seen for Avocet at a budget of $850,000 USD, where prioritizations based on the integrated model captured 2.66% [0.99, 3.66] more expected detections than eBird prioritizations. For most species, the 90% HDI overlapped zero across budgets. Interestingly, the integrated prioritizations performed up to 1.10% [-1.15, -0.97] worse than those based on eBird data alone for Long-Billed Curlew (*Numenius americanus*, Figure 2, Appendix C). When we added monitoring costs to prioritizations based on the integrated model, we found similar patterns to those found when adding monitoring costs to the prioritizations based on professional data only, although the magnitude of the differences was considerably smaller (Appendix B; Figure S5-S6). At the lowest budget of $150,000 USD, the integrated prioritizations yielded an average number of expected detections prioritized up to 53.77% [52.84, 54.53] lower than when using freely available community science data. When monitoring costs were included, the number of expected detections prioritized based on the integrated model were lower than those using community science data across all species and budgets.

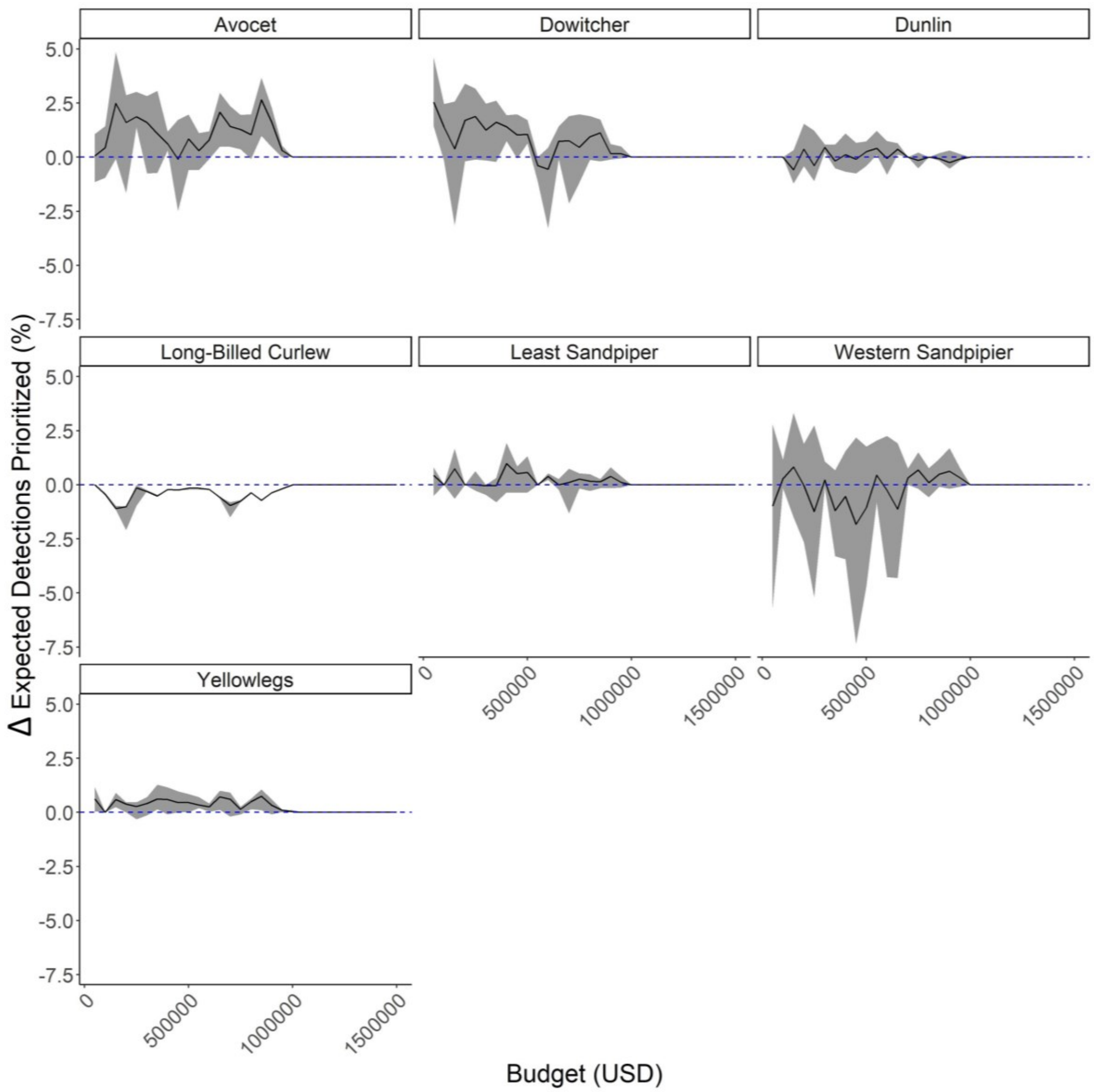

Figure 2. Percent improvement in expected detections prioritized across a range of budgets when basing prioritizations on the best available information (integrated model) compared to prioritizations based on community science data. Solid lines represent the mean difference in the expected detections prioritized between the two prioritizations, and shaded regions represent the 90% high density interval of these contrasts. Positive values indicate that prioritizations based on the integrated dataset performed better, while

negative values indicate that prioritizations based on community science data performed better.

At a set budget of $400,000 USD, using community science data to conduct the prioritizations (and instead using the monitoring portion of the budget on the auction) performed better than using the professional monitoring data (Figure 3). At this budget, all species had between 15-20% more expected detections prioritized when using community science data compared to professional data. The greatest advantage in using the community science data was seen for Least Sandpiper (*Calidris minutilla*), where the difference in performance was 19.04% [16.77, 22.02]. For all species, we found that $120,000 - $130,000 USD in additional spending was required when spending money on professional monitoring to achieve the same outcome that could be achieved using community science data. Therefore, the financial value of community science data in this case study, where the two data types are approximately equal for decision making, is approximately equal to the cost of professional monitoring ($121,622).

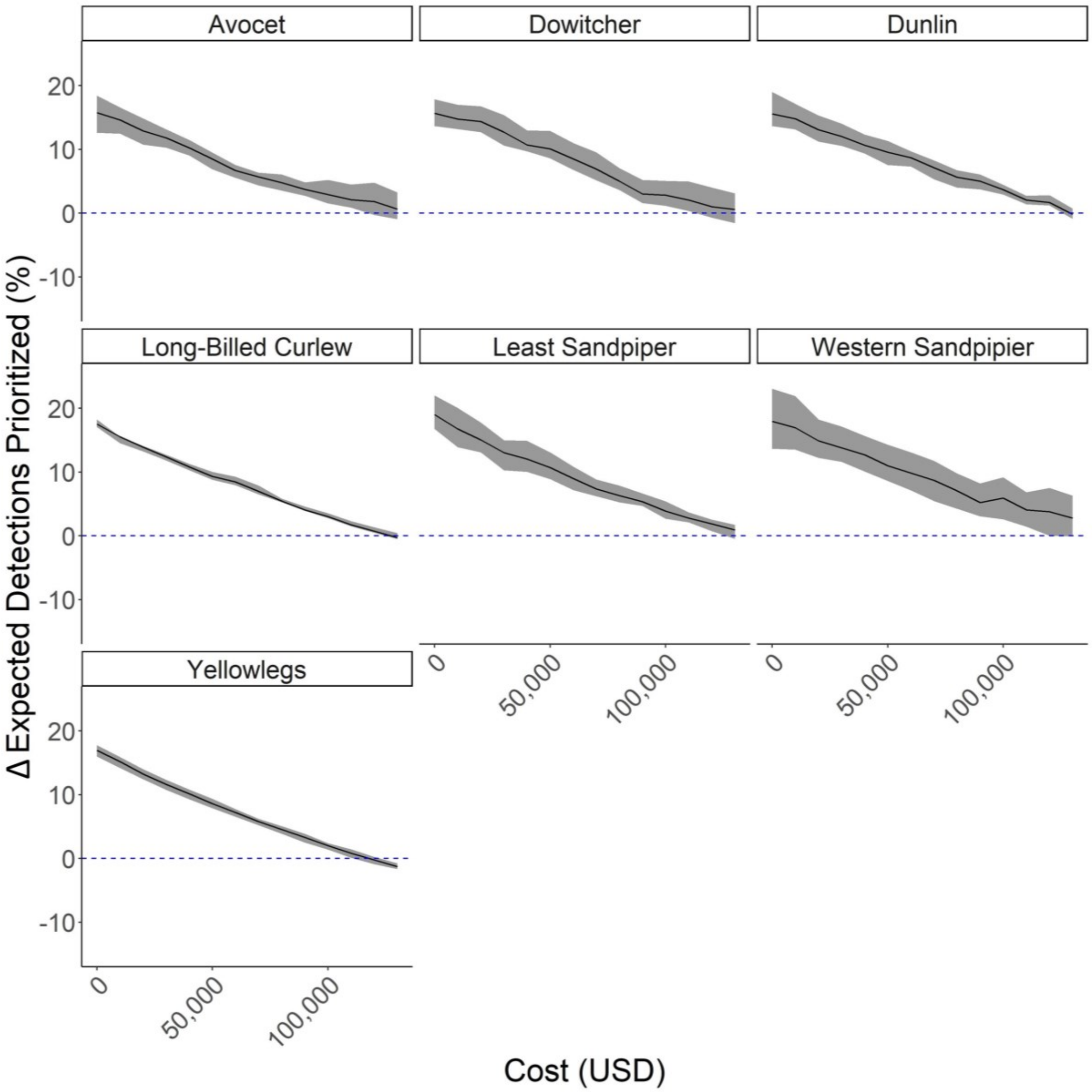

Figure 3. Mean percent difference in expected detections prioritized between community science prioritizations conducted at a budget of $400,000 USD compared to prioritizations derived with professionally-collected data at each incremental increase in the budget beyond $400,000 USD (Cost). Solid lines represent the mean difference in the expected detections prioritized between the two prioritizations, and shaded regions represent the 90% high density interval of these contrasts. Where the 90% HDI bars cross

the blue dotted line, the expected detections prioritized based on community science data is approximately equal to that based on professional data collected by on-site field technicians, at the additional cost along the x-axis.

Discussion

The question of whether to collect more data or act based on what is available should depend on the quality of the available data and, more importantly, whether collecting more (or better quality) data has the potential to improve decision making (Bennett et al. 2018). Though many studies have previously examined the difference in information content between community science programs and more structured, professional monitoring schemes, to our knowledge this is the first comparison that explicitly examines the difference in terms of influencing the outcomes of decisions. Here, we compared the relative value of conservation decisions using biodiversity data collected by community scientists and professional surveyors, explicitly accounting for the cost of professional data collection. For the theoretical decisions in our case study, we found that community science prioritizations performed better than professional monitoring prioritizations across all budgets, and that the advantage was greatest at lower budgets, since the professional data collection costs depleted much of the budget remaining for action. Furthermore, the results of our case study demonstrated that prioritizations based on eBird data performed comparably to those based on the professionally-collected data even without considering the additional cost of professional data collection. This is surprising given that eBird participants are limited in their ability to access these areas, and contradicts expectations that professional monitoring data would perform better due to it being targeted towards the habitats being prioritized. Community science prioritizations also performed comparably to prioritizations based on the integrated dataset, which represents the best available information about the system. Thus, there was a theoretical disadvantage to spending part of the budget on professional monitoring for the purposes of prioritizing action because the community science data was equally capable of informing decisions. This reinforces the concept that both community science and professionally-collected data can be relatively equal in their capacity for the data to inform conservation action in this case, and that the cost spent on monitoring to collect information on biodiversity may detract from the budget remaining for action and therefore diminish biodiversity outcomes.

We found a substantial advantage to using community science data rather than paying for professional biodiversity monitoring in our theoretical case study, both in terms of dollars and biodiversity. However, monitoring requirements are highly contextual (Conlisk et al. 2022), and it is important to acknowledge that monitoring can serve more purposes than simply data collection. Monitoring can be a mandated component of certain environmental programs (Venus and Sauer 2022), and can serve important educational, enforcement and outreach purposes (Likens and Lindenmayer 2018). For example, professional surveyors in the BirdReturns program monitor for both bird presence and adherence to the program requirements, to ensure that adequate habitat is being provided for the focal species. Certain types of data (e.g., on highly cryptic species or in inaccessible places) may also only be collectable using professional monitoring.

Although prioritizations based on the integrated model resulted in slightly better outcomes for certain species, this was not the case when the costs of collecting the professional monitoring data were considered. However, when professional monitoring is mandated or required for other purposes, integrating these data with community science data may help maximize the benefits for biodiversity. In our study, the advantage of using freely available data was substantially lower than the integrated dataset versus the professional dataset alone. We found that prioritizations using community science data performed up to 117% better compared to professional data prioritizations, but only up to 53% better compared to the integrated dataset prioritizations, when the monitoring costs were applied in both cases. The additional information provided by the integrated dataset may also prove to be worth the cost in other contexts.

Previous studies assessing the quality and information content of eBird data support our findings that this community science program demonstrates considerable promise for informing conservation decisions. Several studies have benchmarked measures of species richness (Callaghan et al. 2018), abundance (Feng and Che-Castaldo 2021), diversity (Callaghan et al. 2018; Callaghan and Gawlik 2015), occurrence (Munson et al. 2010; Robinson et al. 2020) and trend (Feng and Che-Castaldo 2021; Horns, Adler, and Şekercioğlu 2018; Walker and Taylor 2017) estimated using eBird data to those estimated using more structured, professionally-collected data. Although there were discrepancies in these estimates in some cases, the eBird data frequently produced similar values to the professionally-collected data. In fact, the eBird models used in this study generally had higher sensitivity and specificity than the models using professionally-collected data (Robinson et al. 2020).. Our results are particularly interesting given that most data from the farms were collected through the TNC point counts, and less commonly by eBird participants. This suggests that models using regional, untargeted eBird data were able to accurately predict species occurrences on the properties of interest, even when data on those particular properties was mostly lacking. Nonetheless, the quality of community science datasets can vary greatly (Boakes et al. 2010), and we urge caution extrapolating these results to other datasets and systems. In addition, although here we assumed data processing effort and costs to be equal, it is important to note that this may not always be the case.

Many factors beyond biodiversity data can influence conservation decision making and outcomes. The cost of obtaining data can substantially influence management decisions (Moore and McCarthy 2010), as can the cost of action (Butt et al. 2020). Prioritizing land for conservation action must also consider the needs of landowners and rights holders, and account for their willingness to participate (Gregory et al. 2012). While our study demonstrates the value of community science for decisions, incorporating these additional factors into would be important in real-world management scenarios.

Conclusions

Our case study demonstrates the financial and ecological benefits of community science data, for helping to redistribute conservation resources from monitoring to action. While many previous studies have compared various biodiversity metrics estimated using community science data to those estimated using professionally-collected data, comparisons in the context of decision science still remain limited. Our results demonstrate that the value of decisions based on a community science dataset was comparable to that based on the best available data, and substantially greater when accounting for monitoring costs. By using high-quality, freely available community science datasets, conservation practitioners may be able to support decisions without depleting the budget remaining to implement conservation action. In our case study, we found this to be true even when the community science data were not collected directly on the properties available for enrollment in the conservation program. This will be critical when budgets are limited. Community science data may not be perfect (no data are), but our study suggests that they can be of sufficient quality for informing decisions about where to prioritize conservation action. We urge practitioners to carefully consider the trade-offs associated with new data collection, and urge consideration of whether existing data may suit their information needs.

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