

## RESEARCH ARTICLE

# Assessing trade-offs in developing a landscape-scale nest monitoring programme for a threatened shorebird

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**Abstract**

1. Effective monitoring of wildlife species requires thorough planning and development of survey programmes that can address management and conservation objectives. Decisions about monitoring programmes include where to survey, survey design and how much effort to allocate at survey sites are typically predicated on limited budgets and available resources. When the scope of inference requires monitoring on a broad spatial scale, predictions of habitat distribution or suitability may be useful for identifying potential survey sites.
2. We focused on a threatened but widely distributed shorebird, the piping plover (*Charadrius melodus*), which is actively monitored across some, but not all of its range. Our objective was to use piping plover habitat distribution maps, which vary annually, to assess the effectiveness of multiple monitoring programme scenarios and their associated costs.
3. In the breeding range, efforts to improve productivity for species of conservation concern often focus on improving probabilities of nest survival. Consequently, collecting adequate nesting data is crucial for obtaining accurate and precise estimates of nest survival and for evaluating the effectiveness of management actions. By simulating the nest monitoring process, we evaluated how much area, where and how often to survey each site when estimating nest survival and detecting effects of potential management actions.
4. As expected, precision increased and bias decreased around nest survival estimates with greater survey coverage and nest visit frequency. We also identified monitoring programmes with negative net values where survey costs outweighed statistical benefits.
5. Although we applied our simulation framework to evaluate nest monitoring designs for piping plovers, it could be extended to assess whether different monitoring programmes can detect changes in the distribution of other species or occupancy of habitats over time.

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## KEYWORDS

community science, cost analysis, management actions, nest survival, piping plover, statistical power, survey design

## 1 | INTRODUCTION

Wildlife monitoring programmes can effectively inform management decisions or measure the outcomes of management actions if the data collected have adequate accuracy and precision to resolve underlying scientific questions (Field et al., 2005; Lindenmayer & Likens, 2010; Reynolds et al., 2011). Forethought and planning are critical for the success of monitoring programmes because failure can result from imprecise objectives, faulty sampling designs or poor data quality (Legg & Nagy, 2006; Sherfy et al., 2011). These issues may result in misguided management and conservation decisions or the loss of institutional support and they may reduce the availability of resources for other research activities or management actions (Reynolds et al., 2011). Funding for wildlife management and conservation biology is increasingly limited, necessitating that monitoring programmes provide the most reliable scientific information for the lowest cost (Reynolds et al., 2011).

Because ecological processes are typically observed incompletely and data are collected as a sample, uncertainty in information derived from data can arise from multiple sources including process stochasticity and observational error (Cressie et al., 2009; Harwood & Stokes, 2003). Process stochasticity may emerge from natural variation in the system, whereas the choice of monitoring and data collection strategies can contribute to observational error. Optimizing monitoring programmes to minimize observational error is therefore useful to reduce data uncertainty and provide more reliable ecological signals. Initial decisions when developing monitoring programmes include where to survey and the amount of resources to allocate. Additionally, when scientific questions of interest require repeated visits to monitoring sites (e.g. to estimate detection or survival probabilities), researchers encounter a trade-off between the number of sites to monitor and the number of repeated surveys at each site (Bailey et al., 2007; MacKenzie & Royle, 2005). To address such monitoring design questions, the expected 'statistical power' (i.e. the ability to detect ecological signals with a given level of confidence) can be compared from different combinations of survey effort and frequency. Decisions about survey designs can then be made by specifying tolerable amounts of data uncertainty and associated survey costs.

Previous studies have evaluated monitoring design effects on various population metrics (e.g. Bailey et al., 2007; Lieury et al., 2017; Lindberg, 2012; Nuno et al., 2013; Reynolds et al., 2011; Southwell et al., 2022). However, evaluations of monitoring programmes designed to collect avian nesting data are lacking. Nest survival is a key parameter contributing to avian productivity and is commonly estimated from field studies. Nest survival is typically defined as the probability that at least one egg hatches (precocial species) or at least one chick fledges (altricial species) from a nest. Substantial

management efforts often go towards providing adequate nesting habitat and reducing nest losses (e.g. from flooding, predation or human disturbances). Management and conservation efforts to improve avian productivity for species of concern often focus on increasing probabilities of nest survival including through nest predator removal (Dinsmore et al., 2014; Garretson & Rohwer, 2001; Pieron & Rohwer, 2010), nest protection using predator exclosures (Anteau et al., 2022; Bailey & Bonter, 2017; Dinsmore et al., 2014) or habitat modifications (Doherty et al., 2014; Dunn et al., 2016). Therefore, collecting adequate nesting data is crucial for obtaining accurate and precise estimates of nest survival and evaluating the effectiveness of management actions.

We developed a generalized simulation framework to evaluate where and how much to survey when estimating nest survival and detecting effects of potential management actions. We applied this simulation framework to assess the performance of multiple monitoring options across a large geographic area, the U.S. Prairie Pothole Region (PPR), for a rare U.S. federally listed shorebird (piping plover; *Charadrius melodus*). This species breeds on unvegetated shorelines of wetlands in the PPR and the locations and amount of nesting habitat are intra- and interannually dynamic and sensitive to changes in water levels and vegetation density (Ellis, Anteau, MacDonald, Swift, Ring, Toy, Sherfy, et al., 2023). Therefore, effective monitoring programmes for piping plovers in the PPR must also be dynamic to respond to changing habitat conditions (McCauley et al., 2016). The ability to detect effects of management actions or changes in breeding productivity that may trigger management actions will lead to more effective recovery efforts for this species.

Our objectives were to evaluate (1) the accuracy and precision of nest survival estimates and (2) the survey costs associated with multiple monitoring scenarios. We varied the spatial coverage of nest monitoring surveys and the frequency of repeated visits within each proposed monitoring scenario. We simulated the effect of a hypothetical management action and assessed the statistical power of each proposed programme by quantifying our ability to detect an effect of management actions on nest survival. We predicted that monitoring scenarios with higher levels of effort (survey coverage and/or frequency) would have greater statistical power, but these gains may be offset by higher costs, and therefore, intermediate levels of effort may balance this trade-off. A potential benefit of using a framework like ours to design a monitoring programme is that relying on remotely sensed habitat information can lead to more dynamic identification of survey sites and allow for the updating of habitat availability estimates with limited field effort. Lastly, we report the outcomes of one pilot demonstration using remotely sensed habitat predictions to direct a single-season field effort and we compared the costs associated with this field effort and our simulated monitoring programmes.

Although we applied our simulation framework to evaluate nest monitoring programmes for piping plovers in the PPR, a similar approach could be adapted to inform study designs for large-scale nest monitoring programmes where nest survival or breeding bird occupancy are parameters of interest.

## 2 | MATERIALS AND METHODS

### 2.1 | Simulation strategy

We based our simulation framework on predictions of nesting habitat and breeding intensity for piping plovers in the PPR generated from a habitat selection model (Ellis, Anteau, MacDonald, Swift, Ring, Toy, Sherfy, et al., 2023). This model was informed by integrating piping plover nesting data collected over a 20-year period (2000–2019) and observations of piping plovers from eBird, an online database of global bird observations collected by community scientists (Sullivan et al., 2009). Based on temporally dynamic maps of predicted breeding distribution of piping plovers across the PPR, we simulated survey efforts under multiple monitoring scenarios by identifying potential nesting areas from spatial predictions. We simulated plausible nest locations that could have occurred based on annual changes in habitat availability. We simulated the nest monitoring process to investigate the precision and accuracy of nest survival estimates resulting from multiple monitoring scenarios. The simulation framework was divided into four steps: (1) using spatially explicit predictions of nesting habitat to identify high priority areas to survey based on the predicted relative density of nests; (2) simulating an observation model, which represented the discovery and monitoring of simulated nests based on multiple monitoring scenarios; (3) analysing the survival of nests from simulated monitoring data; and (4) assessing bias and precision of nest survival estimates, statistical power and survey costs (Figure 1).

The simulation was primarily based on repeated visits to multiple sites (i.e. survey cells) to search for and monitor the fate of nests. We

designed multiple scenarios for a monitoring programme by varying three components of survey effort that collectively represent 18 possible monitoring scenarios:

#### 2.1.1 | Number of survey cells

The number of survey cells visited in a single breeding season had three possibilities (100, 200 or 400).

#### 2.1.2 | Size of surveys

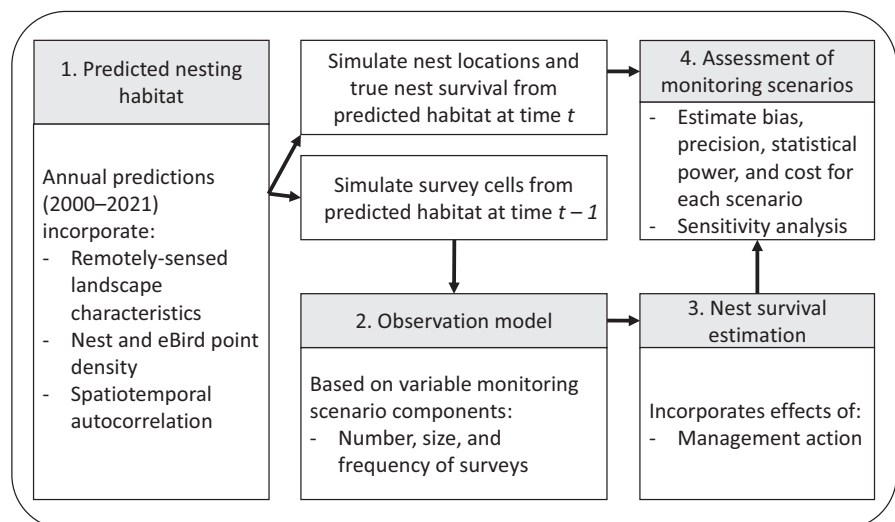
The size, or coverage, of each survey had three possibilities (3×3, 6×6 or 9×9-km survey cells—hereafter referred to as 3-, 6- and 9-km survey cells). We selected these sizes based on the approximate maximum distance a single surveyor could cover in an 8-hr working day (≈9 km). We based this decision on our own field experiences and with an assumption that nesting habitat would occur along linear shorelines (not distributed throughout an entire cell) and habitat suitability for nesting within survey areas would be heterogeneous.

#### 2.1.3 | Survey frequency

Survey frequency represented the rate of return to each survey cell in a single season to monitor the fate of nests. We set two possibilities for survey frequency (1 or 2 days/week).

### 2.2 | Nesting habitat predictions

We used results from Ellis, Anteau, MacDonald, Swift, Ring, Toy, Sherfy, et al. (2023), which included annual (2000–2021) spatial predictions of piping plover nesting habitat in the PPR at a 30-m resolution. These predictions were generated using an integrated point



**FIGURE 1** Conceptual diagram of simulation procedures and assessment of different monitoring scenarios.

process model (Isaac et al., 2020) informed by piping plover nesting locations and eBird observations. Point process models can be used to evaluate the patterns of habitat selection and to estimate an intensity surface of the density of observations within an area (Renner et al., 2015). In our case, continuous values of the intensity surface characterized the predicted intensity of breeding piping plovers in each 30m pixel based on underlying landscape features.

The integrated point process model used to develop the habitat predictions incorporated effects of landscape characteristics that changed annually (vegetation coverage, surface water levels and land cover composition) and characteristics that remain relatively static over time (slope and distance to wetland basins, roads or human settlements; Ellis, Anteau, MacDonald, Swift, Ring, Toy, Sherfy, et al., 2023). Further details about the modelling process, including data collection, the study area, spatial scales and measurement of landscape predictor variables, model development and model validation, are in Ellis, Anteau, MacDonald, Swift, Ring, Toy, Sherfy, et al. (2023). To identify pixels with habitat conditions that could support nesting and have high predicted intensities of breeding piping plovers, which would be of high priority to survey, we identified a suitability threshold value from continuous prediction layers (Ellis, Anteau, MacDonald, Swift, Ring, Toy, Sherfy, et al., 2023). The suitability threshold was identified using the symmetric extremal dependence index (Ferro & Stephenson, 2011), which is similar to the true skill statistic and can be used to test how well species distribution models separate true presences from absences (Allouche et al., 2006).

### 2.3 | Simulating surveys

The first step in the simulation process was to randomly select a year of interest. When simulating the survey effort, we used the prior year's nesting habitat prediction to replicate what may occur in real-world situations. Remotely sensed data layers and imagery describing habitat conditions are often acquired after a breeding season and surveys would be directed towards high priority areas identified from the conditions in the previous year. Therefore, the possible years to simulate survey efforts were 2001–2021. We aggregated 30m pixels to 3, 6 or 9km cells using the maximum cell value (i.e. if larger cells contained any 30m pixels with high predicted intensities of breeding piping plovers) and then, depending on the monitoring scenario, randomly selected 100, 200 or 400 of these cells to be surveyed. This aggregation strategy prevented survey cells from overlapping.

### 2.4 | Simulating nest survival and nest monitoring histories

We placed 300 nest locations within suitable nesting areas based upon nesting habitat predictions generated from the intensity surface from the year of interest. The mean number of piping plover

nests found in the PPR between 2000 and 2019 was 231 per year (S.D.=74.4; Ellis, Anteau, MacDonald, Swift, Ring, Toy, Sherfy, et al., 2023). Therefore, we simulated a sample of 300 nests to account for nests that were likely present but never found during surveys. We assumed a 122-day nesting season (e.g. April 15 to August 15) and simulated nest initiation dates for each nest using a normal distribution with day-of-season 42 as the mean (e.g. May 27 with April 15 as day 1), and standard deviation of 12 days (Anteau et al., 2022). We assumed a 35-day exposure period from nest initiation to hatch (Anteau et al., 2022).

We considered two possibilities when setting cumulative nest survival probabilities (probability that at least one egg hatches) and ran all monitoring scenarios twice with either a high (0.6) or low (0.3) survival probability as the intercept. We also included nest-specific random noise to incorporate unmodelled variability on daily nest survival (normally distributed with mean=0, S.D.=0.2 on the logit scale; mean and 95% quantiles of variability on the probability scale=0.5, 0.4–0.6). Additionally, we simulated the effect of a hypothetical management action (in practice, actions often involve nest protection efforts such as predator exclusions; Anteau et al., 2022) where each discovered nest had a 50% chance of receiving the action and the action had a positive effect on daily nest survival probabilities ( $\beta_{\text{manage}}=0.2$  on the logit scale). To account for potential survey bias from nests that may be more likely to fail late in the nesting season or soon after initiation, we included a positive effect of nest age ( $\beta_{\text{age}}=0.1$  on the logit scale) and a negative effect of nest initiation date ( $\beta_{\text{date}}=-0.1$  on the logit scale) on daily survival probabilities (Anteau et al., 2022). We simulated nest exposure histories using binomial trials with nest-specific daily survival probabilities using an approach similar to Weiser (2021).

We overlaid nest points on survey cells to determine which nests would be available to be detected and which nests would be outside of survey cells. We assumed that each survey cell would be visited either once or twice per week during the 122-day nesting season. We matched survey visits with nest exposure histories to identify nests that would be active in each survey cell during visits and to generate nest monitoring histories. We considered that initial nest detection would be imperfect and set the probability of detecting each nest using a beta probability distribution to constrain values between 0 and 1 with shape parameters  $\alpha=30$  and  $\beta=30$  (mean=0.50, S.D.=0.064). Nest detection probabilities for piping plovers nesting on river habitats range from 0.41 to 0.65 (Shaffer et al., 2013), compared to other ground-nesting shorebird species nesting on wetlands that range from 0.21 to 0.64 (Smith et al., 2009). After the first detection, the probability of relocating a nest was set to 1. Because we assumed imperfect detection and one or two survey visits per week, a portion of the simulated nests may have failed or hatched without being located. We used R 4.1.3 (R Core Team, 2021) to simulate data and the *sp* (Bivand et al., 2013; Pebesma & Bivand, 2005) and *raster* (Hijmans, 2022) packages to integrate spatial data. Annual (2000–2021) spatial predictions of piping plover nesting habitat are available as a USGS data release (Ellis, Anteau, MacDonald, Swift, Ring, Toy, & Sherfy, 2023).

## 2.5 | Effectiveness of monitoring plans analysis

We used a logistic-exposure model (Shaffer, 2004) to analyse each simulated nest monitoring data set and included a binary covariate indicating if nests received the management action to test for the effect of that action on nest survival. We applied the logistic exposure model in a Bayesian framework using JAGS 4.3.0 (Plummer, 2003) with the *jagsUI* package (Kellner, 2019) in R. We used uninformative normal priors (mean=0, S.D.=2 on the logit scale) for the intercept,  $\beta_{\text{manage}}$ ,  $\beta_{\text{age}}$  and  $\beta_{\text{date}}$  (Northrup & Gerber, 2018). For each simulation, we generated four chains of 1000 iterations and discarded the first 500 and did not thin, resulting in 2000 saved iterations to generate posterior distributions of parameters. These settings were sufficient for model convergence (Gelman-Rubin diagnostic <1.10 and visual inspection of mixing of chains from traceplots; Gelman & Rubin, 1992).

We ran 500 replicates for each of the 18 monitoring scenarios under both high and low nest survival probabilities (36 total scenarios). In each replicate, we recorded (1) the bias of estimated nest survival (absolute difference between estimated and true mean nest survival probabilities), (2) the imprecision of estimated nest survival (coefficient of variation: CV), (3) the proportion of  $\beta_{\text{manage}}$  posterior distribution (effect of management action) that was positive, (4) the percentage of nests that fell outside of survey cells, (5) the percentage of nests within survey cells that were not detected, (6) the total cost of the surveys and (7) the randomly selected sampling year (to assess interannual variability). We considered that a replicate successfully detected the effect of the management action if >85% of the  $\beta_{\text{manage}}$  posterior distribution was positive and we counted the proportion of successful replicates in each monitoring plan scenario as the statistical power to detect effects of management actions. We calculated the cost of each 3-, 6- and 9-km survey cell as 1/3, 2/3 and one 8-h working day (assuming a linear walking survey) so that the total cost was the sum of survey visits multiplied by the number of person working days required to survey each cell. In practice, field crews may discontinue survey visits or reduce the amount of time spent in cells when no birds are observed throughout a nesting season. Therefore, we assumed that unoccupied survey cells (no nest points located within its boundaries within a nesting season) would require less effort after the first visit when calculating costs. For unoccupied survey cells, we reduced the survey costs for revisits (not the first survey) within a single nesting season by 1/2. Estimates of the number of required working days represent relative, not absolute, costs of survey designs.

We used linear models to evaluate how the three components of monitoring design (number, size and frequency of surveys) affected four performance metrics: proportion of replicates in which a significant positive effect of management action was detected, the bias and imprecision of estimates of nest survival, and monitoring costs. We assessed the relative contributions of monitoring scenario components (number, size and frequency of surveys) to changes in the four performance metrics above. We scaled monitoring plan

components to have a mean of zero and standard deviation of one to estimate unit-less effect sizes that we used to infer the relative importance of monitoring scenario components on the four performance metrics. We normalized statistical power ( $\Delta\text{power}$ =the difference between the statistical power of a given monitoring scenario and the minimum power across all scenarios divided by the difference between the maximum power across all scenarios and the minimum power across all scenarios) and costs ( $\Delta\text{cost}$  calculated the same as  $\Delta\text{power}$ ) to estimate the net value of each monitoring scenario. Therefore, the net value of each monitoring scenario was calculated as  $\Delta\text{power} - \Delta\text{cost}$ , such that negative values indicate that the costs of a monitoring scenario outweighed its statistical power.

Lastly, we considered the cost and effectiveness of each monitoring plan if repeated visits did not occur (therefore, estimating nest survival would not be possible) to simulate counting breeding adult piping plovers. We assumed that if a nest was present at some point during the nesting season within a survey area, the probability of detecting a breeding adult would be 1, with the assumption that breeding adults would remain near nesting sites throughout the breeding season. Surveys to count breeding adult piping plovers can be sensitive to survey timing and estimates that do not incorporate counts of broods and fledglings can be biased (Baasch et al., 2015; Shaffer et al., 2013). Therefore, we used the percentage of nests that fell outside of survey cells to approximate the effectiveness of single survey visits. We calculated the cost of single-visit surveys as the total number of survey points multiplied by the effort at each survey (1/3, 2/3 and 1 for 3, 6 and 9 km cells, respectively).

## 2.6 | Pilot demonstration

We tested the feasibility of our framework to inform a field effort in 2021. We aggregated 30m pixels to 300m resolution using the maximum 30m pixel value, creating a grid of 300m survey cells across the PPR. We used a stratified random sampling approach to ensure surveys were conducted where piping plovers had been observed previously and in previously unsurveyed locations where habitat predictions indicated nesting habitats were suitable. We categorized pixels as 'known' or 'unknown' based on whether they fell within either 10km of a known nesting location or an eBird record. We randomly placed 400 survey starting points in survey cells with high predicted breeding intensity (>90th percentile of 300m cell values) and placed 200 points in known cells and 200 in unknown cells. Given logistical constraints (e.g. land ownership and access), we attempted to survey known and unknown cells equally. At each cell, surveyors recorded their start and end time, habitat conditions in the cell and any piping plover observations (counts of adults and juvenile as well as adult behaviours). We did not focus on monitoring nests as the primary goal of the pilot demonstration was to assess the minimum cost to visit each site once. A complete standard operating procedure, including steps to create survey cells and survey starting points as well as field procedures for nest searching and monitoring, can be found in the [Supporting Information](#).



### 3 | RESULTS

Survey costs were negatively correlated with percent of nests outside of survey cells and percent of nests within survey cells that hatched or failed prior to detection ( $r = -0.81$  and  $-0.77$ , respectively). CV (i.e. imprecision) was positively correlated with percent of undetected nests within survey cells ( $r = 0.78$ ) and moderately correlated with percent of nests within survey cells ( $r = 0.56$ ) and survey cost ( $r = -0.51$ ). Other combinations of metrics that we used to assess the performance of monitoring plans were uncorrelated ( $r < |0.5|$ ). Survey year contributed minimally to variation in CV (overall mean = 0.163, annual range = 0.160–0.167), bias (0.054, 0.051–0.056), power to detect management effects (0.77, 0.75–0.79), percent of nests outside of survey cells (65%, 64%–67%) and percent of undetected nests within survey cells (20%, 19%–21%).

Precision of nest survival probabilities, bias of nest survival probabilities, proportion of  $\beta_{\text{manage}}$  posterior distributions that were positive, and survey costs were all sensitive to changes in monitoring scenario components, although the magnitude of the effect and relative importance of these components varied (Table 1). The mean CV for estimates of overall nest survival across all monitoring scenarios when survival probabilities were low was 0.21 (95% quantiles = 0.12–0.39) and 0.12 (0.07–0.22) when survival probabilities were high (Table 1, Figure 2). When survival probabilities were low, CV was most sensitive to visit frequency (relative importance = 0.45), whereas when survival probabilities were high, CV was most sensitive to the number of survey cells (relative importance = 0.41; Table 1). Bias was similar between high and low nest survival scenarios and was most sensitive to the number of survey cells (Table 1, Figure 2). When 100 surveys were conducted, mean bias was 0.071 (95% quantiles = 0.002–0.209) and 0.004 (0.002–0.113) when 400 surveys were conducted (Figure 2).

The effect of the management action on nest survival was detected in >50% of simulations when survival probabilities were low, but not when survival probabilities were high (proportion of simulations where >85% of  $\beta_{\text{manage}}$  posterior distributions were positive = 0.56 and 0.46, respectively; Figure 3). Similar to CV, the proportion of  $\beta_{\text{manage}}$  posterior distributions that were positive was most sensitive to visit frequency when survival probabilities were low but was most sensitive to the number of surveys when survival probabilities were high (Table 1, Figure 3). Survey costs increased at a higher rate when the number or size of surveys increased than when the visit frequency increased (Table 1, Figure 3).

The mean percent of nests within survey cells that were undetected (failed or hatched without being detected) was greater when the visit frequency was 1 day/week (27%, 95% quantiles of 9000 replicates = 12%–44%; 2 days/week = 13%, 3%–26%) and when survival probabilities were low (25%, 10%–44%; high survival probabilities = 14%, 4%–30%; Figure 4). The mean percent of nests outside of survey cells ranged between 20% and 73% when varying the number and size of surveys (Figure 3). The lowest cost monitoring scenario where most nests were within survey cells used

400, 3-km surveys (mean cost for 1 visit/week = 780 person working days, mean cost for 2 visits/week = 1560 person working days; Figure 3). The monitoring scenario with the greatest net  $\Delta\text{power} - \Delta\text{cost}$  across all nest survival and visit frequency scenarios was 400, 3-km surveys (Figure 5). Two scenarios resulted in a negative net  $\Delta\text{power} - \Delta\text{cost}$ , indicating that the proportional gain in statistical power did not exceed the proportional gain in survey costs (Figure 5). Single-visit costs ranged from 33 working days (100, 3-km surveys) to 400 working days (400, 9-km surveys; Figure 6) and the lowest cost monitoring option where >50% of nests were within survey cells was 400, 3-km surveys.

#### 3.1 | Pilot demonstration

In 2021, we conducted single visit surveys at 400, 300m cells distributed across the PPR in North Dakota, South Dakota and Montana that included 170 cells in unknown piping plover areas and 230 in known areas. Most sites were surveyed as a cluster with adjacent cells (91%), and joining these clustered cells resulted in 158, 3-km surveys; 145, 6-km surveys; and 136, 9-km surveys. We observed 83 piping plovers, including 73 adults and 10 juveniles across 36-person working days, which is consistent with our simulated estimates for single-visit surveys (Figure 6).

### 4 | DISCUSSION

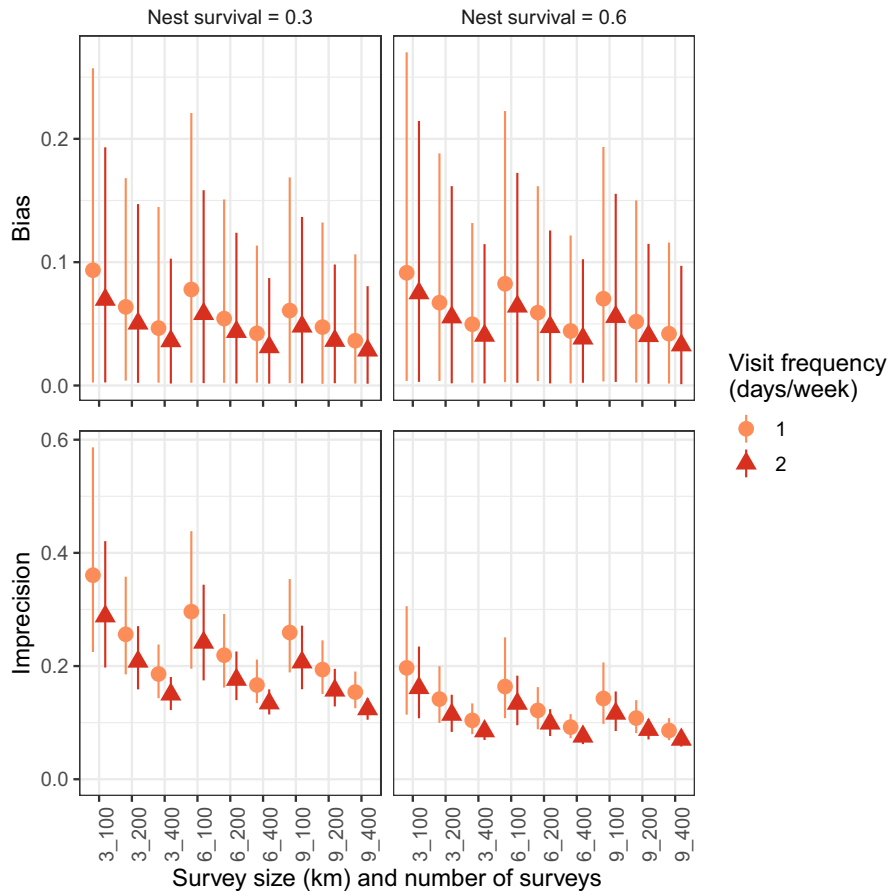
We used a simulation framework to investigate the performance of a set of 18 nest monitoring scenarios for piping plovers under two nest survival probabilities (36 total comparisons). This framework allowed us to predict differences among monitoring scenarios without the need to implement numerous, expensive field studies. We also provide information for decision makers so they can better understand trade-offs associated with different survey options and choose the most appropriate monitoring scenario based on their goals and constraints. We identified a monitoring scenario that consistently had the highest net value under both high and low nest survival conditions and visit frequencies (400, 3-km surveys). This scenario includes less time in terms of working days at more survey sites which should lead to proportionally more nests being monitored at a comparable cost to other scenarios. As expected, bias increased and precision decreased as the size or number of surveys were reduced, more nests were missed and when nests were visited less frequently. Even under the most extensive and costly monitoring scenario, some nests were missed or undetected, indicating that a complete census was not possible from the scenarios we considered (Shaffer et al., 2013). Additionally, we identified monitoring scenarios where the survey costs outweighed the benefits of statistical power. When the strengths and limitations of different methods for monitoring the focal species' productivity are understood, varying levels of survey effort can continue to produce reasonable estimates of abundance and

**TABLE 1** Estimates, 95% quantiles and relative importance of four metrics used to assess the performance of multiple monitoring options across a large geographic area, the U.S. Prairie Pothole Region, for a U.S. federally listed shorebird (piping plover; *Charadrius melodus*). We fit linear models to imprecision (coefficient of variation), bias (absolute difference between true and estimated nest survival probabilities), the effect of management action (proportion of  $\beta_{\text{manage}}$  posterior distributions that were positive) and survey costs (person working days) from 18,000 replicates (500 per scenario) to compare the sensitivity of these performance metrics to components of the monitoring scenarios under both high and low nest survival probabilities. Survey size (3, 6 and 9 km), number (100, 200 or 400), visit frequency (1 or 2 days/week) and mean nest survival probabilities (0.3 and 0.6) varied depending on the scenario. All components of the monitoring scenario were scaled (mean=0, standard deviation=1) for comparative purposes.

Parameter	Coefficient estimate	2.50%	97.50%	Relative importance
<i>Coefficient of variation</i>				
Nest survival=0.3				
Intercept	0.21	0.21	0.21	
Size	-0.02	-0.03	-0.02	0.25
Number	-0.03	-0.03	-0.03	0.30
Visit frequency	-0.04	-0.04	-0.04	0.45
Nest survival=0.6				
Intercept	0.12	0.12	0.12	
Size	-0.01	-0.01	-0.01	0.26
Number	-0.02	-0.02	-0.02	0.41
Visit frequency	-0.02	-0.02	-0.02	0.33
<i>Absolute difference from true value</i>				
Nest survival=0.3				
Intercept	0.05	0.05	0.05	
Size	-0.01	-0.01	-0.01	0.27
Number	-0.01	-0.01	-0.01	0.38
Visit frequency	-0.01	-0.01	-0.01	0.35
Nest survival=0.6				
Intercept	0.06	0.05	0.06	
Size	-0.01	-0.01	-0.01	0.24
Number	-0.01	-0.01	-0.01	0.47
Visit frequency	-0.01	-0.01	-0.01	0.29
<i>Proportion of <math>\beta_{\text{manage}}</math> that was positive</i>				
Nest survival=0.3				
Intercept	0.79	0.79	0.80	
Size	0.03	0.02	0.03	0.26
Number	0.03	0.03	0.04	0.31
Visit frequency	0.04	0.04	0.05	0.43
Nest survival=0.6				
Intercept	0.74	0.74	0.75	
Size	0.03	0.02	0.03	0.27
Number	0.04	0.03	0.04	0.40
Visit frequency	0.03	0.03	0.04	0.33
<i>Person working days</i>				
Nest survival=0.3				
Intercept	1342.04	1332.96	1351.15	
Size	546.73	537.72	555.74	0.32
Number	723.28	714.27	732.29	0.42
Visit frequency	448.03	439.02	457.04	0.26
Nest survival=0.6				
Intercept	1384.75	1375.51	1394.00	
Size	567.26	558.02	576.51	0.32
Number	742.29	733.05	751.54	0.42
Visit frequency	461.36	452.11	470.60	0.26

productivity (Farrell & Baasch, 2020). Piping plover habitats in the PPR cover more than 700,000 km<sup>2</sup> of the North American midcontinent and monitoring resources are often limited and our results

indicate that monitoring designs for this sensitive species can be flexible according to available budgets, while providing similarly accurate estimates of productivity.



**FIGURE 2** Bias (absolute difference between estimated and true mean nest survival probabilities) and imprecision (coefficient of variation of nest survival probabilities) of replicates under each monitoring scenario for a threatened shorebird (piping plover; *Charadrius melodus*). Points show the mean from simulations with 95% quantiles as error bars.

Our simulation analysis indicated that visit frequency had a consistent effect on the bias and precision of nest survival estimates and the power to detect effects of management actions, particularly when nest survival was low. Increasing the frequency of survey visits can reduce the uncertainty associated with the timing of nest completion and assignment of nest fate and reduce detection biases towards successful nests (Shaffer et al., 2013). However, the frequency of repeated visits was not the most influential component on survey costs of the monitoring scenarios we tested. These results suggest that minimizing survey costs by reducing the frequency of nest visits to once a week may provide less of a cost benefit and incur a greater consequence on parameter estimation than if the number or size of surveys were reduced. An alternative motivation for reducing visit frequency may be to minimize investigator disturbances around nest sites (Götmark, 1992), particularly if these disturbances lead to reduced reproductive success (Mayer-Gross et al., 1997; Meixell & Flint, 2017). In these instances, nest temperature data loggers (Stephenson et al., 2021) or nest cameras (Andes et al., 2019; Ellis et al., 2018; McKinnon & Bêty, 2009) may be beneficial for monitoring nests and reducing investigator visit frequencies. The added costs of such devices may be offset by reducing investigator time in the field and uncertainty in assignments of nest fate (Ellis et al., 2018) or the timing of nest failure.

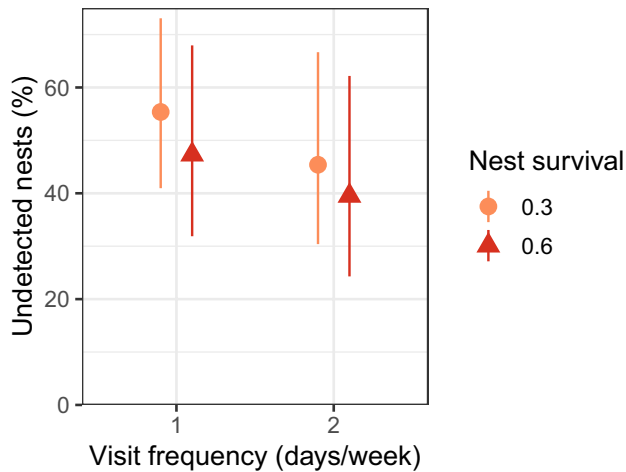
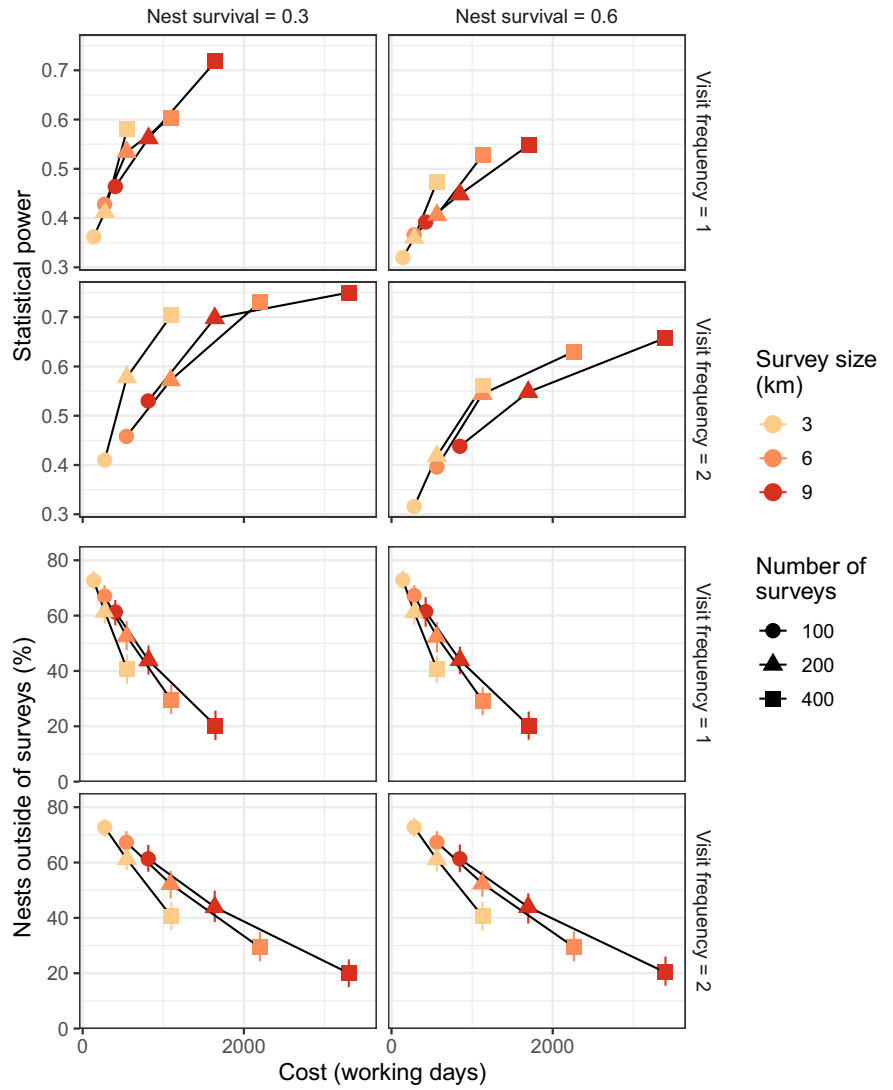
We found that the relative importance of monitoring scenario components varied based on overall nest survival rates. For

example, visit frequency had the greatest influence on precision and statistical power when nest survival was low, but the number of surveys had the greatest influence on precision and statistical power when nest survival was high. These findings indicate that there may be benefits to implementing adaptive monitoring designs, such that monitoring designs evolve in response to changing environmental conditions, management objectives or monitoring tools (Lindenmayer & Likens, 2009). Based on our findings, visit frequency could be prioritized when more nests are anticipated to fail (e.g. early in the breeding season, in certain years or in certain regions within a study area) and survey coverage could be prioritized when nest survival is expected to be highest.

Most monitoring programmes are designed according to available staff or budgetary resources, without assessing precision around parameter estimates or statistical power to detect changes in estimates that may result (Legg & Nagy, 2006). Management decisions influencing nest survival will be most effective if changes in survival from threats or management actions are detected as soon as possible. We found that half (49%) of our simulations failed to detect the positive effect of the management action after one season. Failing to detect a positive effect of management actions will potentially lead to a loss of support for such actions and missed conservation opportunities, particularly when those actions carry additional implementation costs (Legg & Nagy, 2006). Therefore, understanding the statistical power of a monitoring programme up front can help to clarify the monitoring effort and length of study necessary



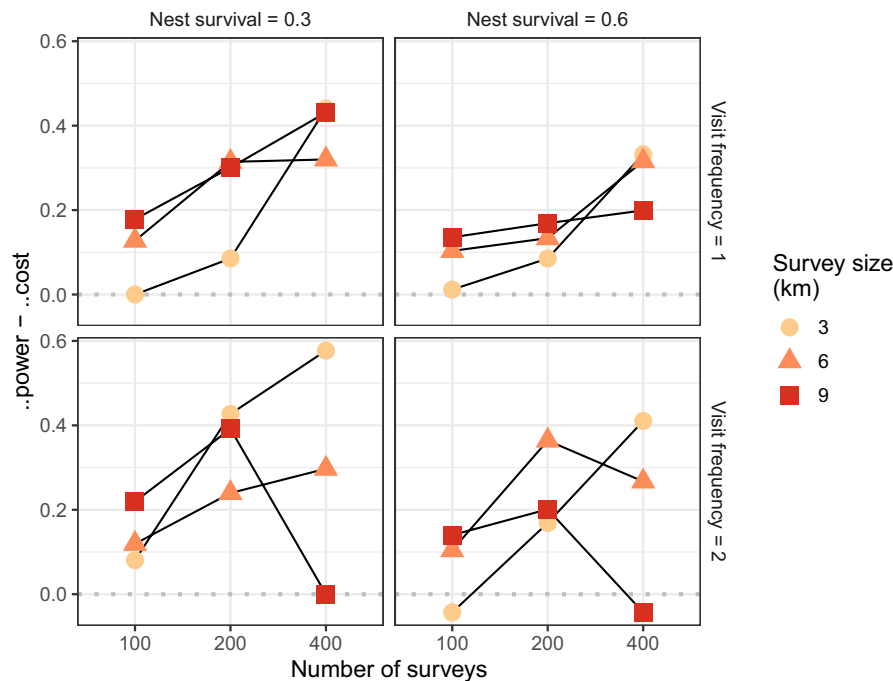
**FIGURE 3** Statistical power (proportion of replicates out of 500 where >85% of  $\beta_{\text{manage}}$  was positive) and the percentage of nests outside of survey cells by survey costs (number of person working days) under each monitoring scenario for a threatened shorebird (piping plover; *Charadrius melodus*). Visit frequency refers to days/week. Black lines connect points with the same survey size. Points show the mean from simulations with 95% quantiles as error bars.



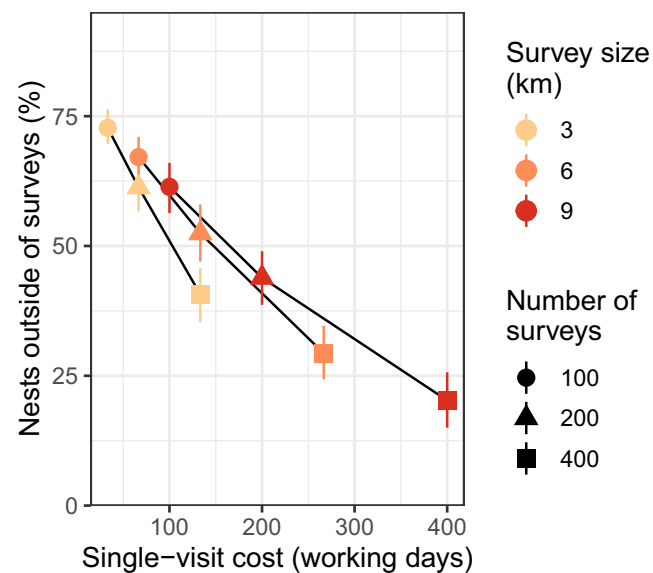
**FIGURE 4** Percentage of undetected nests (nests within survey cells that failed or hatched without detection, therefore, percentages were invariant across the size and number of surveys) when surveys were conducted one or two times per week, under high and low nest survival scenarios for a threatened shorebird (piping plover; *Charadrius melodus*). Points show the mean from simulations with 95% quantiles as error bars.

for resolving underlying scientific questions such as whether a management action is effective (Reynolds et al., 2011).

Predicted distributions of piping plover nesting habitat used as the basis for simulation in our study were informed by both nesting and eBird locations (Ellis, Anteau, MacDonald, Swift, Ring, Toy, Sherfy, et al., 2023). The increasing use of publicly available, community science data (inclusive of any volunteer participant; Cooper et al., 2021) in ecological studies warrants an assessment of survey designs that may be informed by this type of data, particularly if a goal is to inform conservation or management decisions (Stuber et al., 2022; Sullivan et al., 2017). Community science data are typically abundant and species observations outside of established monitoring sites may entice researchers to allocate study resources confirming new observations. We provided a case study to show how predicted habitat distributions based on data collected during targeted nesting surveys, which were limited in spatial scope, and community science data, which filled critical spatial gaps, could be used to inform a more statistically designed monitoring programme. The use of community science data for management decisions or policymaking has so far been limited, likely due to uncertainties



**FIGURE 5** Net values of statistical power minus survey costs for each monitoring scenario for a threatened shorebird (piping plover; *Charadrius melodus*). Statistical power and survey costs were normalized (ranging between 0 and 1) and negative values indicate scenarios where survey costs outweigh statistical power. The dotted grey line delineates 0, where survey costs and statistical power are balanced. Black lines connect points with the same survey size. Visit frequency refers to days/week.



**FIGURE 6** Percentage of nests outside of survey cells by the costs (number of person working days) when visiting each survey cell once (and not monitoring nest fates) for each monitoring scenario for a threatened shorebird (piping plover; *Charadrius melodus*). Black lines connect points with the same survey size. Points show the mean from simulations with 95% quantiles as error bars.

about the scientific rigour of these data. However, community science data have been validated against targeted biological monitoring programmes and can provide comparable information at regional or national scales (Stuber et al., 2022).

The optimal monitoring scenario in our simulation analysis was dependent on assumptions of our simulation and study system; therefore, our results may change if costs were calculated differently or in systems where the spatial configuration of nesting habitats

differs from ours. Given that we considered costs to be relative, not absolute, and we considered survey time but not travel time to survey sites when calculating costs, actual costs would be greater, and therefore, net values for some monitoring plans could become negative if travel costs were included, particularly across our large study area. Depending on the spatial configurations of survey cells and field crews and the number of surveyors in field crews, travel times could vary widely. Piping plover habitats are widely distributed in the PPR, but nests are often concentrated within 'hotspots' (Ellis, Anteau, MacDonald, Swift, Ring, Toy, Sherfy, et al., 2023). This type of aggregation of nests across space is common for species that use patches of habitat distributed across large areas, for species exhibiting colonial or semi-colonial nesting behaviours (Dardenne et al., 2013; Gibbs, 1991; Patrick, 2013), and where social cues or community interactions contribute to the spatial pattern of nests, in addition to habitat conditions (Cunningham et al., 2016; Samplonius & Both, 2017; Swift et al., 2017, 2023). Therefore, precision and bias will likely differ with varying aggregation and spatiotemporal autocorrelation of nest patterns and available habitats (Blanchard et al., 2008).

Designing effective landscape-scale monitoring programmes requires cooperation between decision makers and researchers to formulate study objectives and information needs while simultaneously understanding trade-offs between possible information loss, error rates and costs (Reynolds et al., 2016). Our research provides insights into how it is possible to improve nest monitoring plans and implement informed management actions while taking into consideration observation error and monitoring uncertainties. The simulation framework from our case study could be used in a range of ecological systems, if sufficient predictions of species distributions, habitat use or habitat suitability across a region of interest were available. Preliminary indices of habitat suitability using expert knowledge or maps based on community science data (e.g. eBird Status and Trends

abundance maps; Fink et al., 2021) could be used and updated as targeted data are collected (Southwell et al., 2022). While we did not use our study to assess whether different monitoring plans could detect changes in the distribution or occupancy of nesting habitats over time, our simulation framework could be extended to apply simulated nests that were detected in habitat use or occupancy analyses rather than nest survival analyses as we did here.

## AUTHOR CONTRIBUTIONS

All authors contributed to the study conception and design. Kristen S. Ellis conducted the data analyses and wrote the first draft of the manuscript. Megan M. Ring and Garrett J. MacDonald conducted the pilot field effort. All authors reviewed and approved the final manuscript.

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## CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interests.

## PEER REVIEW

The peer review history for this article is available at <https://www.webofscience.com/api/gateway/wos/peer-review/10.1002/2688-8319.12308>.

## DATA AVAILABILITY STATEMENT

Nesting habitat maps used in this study are available as a USGS data release: <https://doi.org/10.5066/P9KWK13B> (Ellis, Anteau, MacDonald, Swift, Ring, Toy, & Sherfy, 2023).

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## SUPPORTING INFORMATION

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

**Supporting Information S1.** Monitoring Breeding Piping Plovers in the Alkaline Wetlands.

**Supporting Information S2.** Using spatial habitat predictions to inform survey efforts.

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