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Original Research Article

Detection of local-scale population declines through optimized tidal marsh bird monitoring design

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ABSTRACT

Evaluating the efficacy of monitoring designs is crucial for the successful monitoring and conservation of populations. For tidal marsh bird species of conservation concern, detecting population declines at local spatial scales within actionable time frames is a top priority. We examined and compared the effectiveness of alternative monitoring strategies for detecting local-scale population declines using count data from 1176 spatially-independent salt marsh sampling points throughout the northeastern United States (Maine to Virginia). We used abundance estimates that accounted for imperfect detection as initial conditions to simulate annual population declines of 5%, 10%, 30%, and 50% over a 5-year sampling period. Under an optimal monitoring design with biennial sampling, we were able to successfully detect annual population declines of ≥30% for each species and for all species combined. However, this required a minimum of 15–20 points per site being sampled. Power to detect declines, although low for detecting smaller annual declines (i.e., <10%), improved substantially when points were visited twice per season, yet a third visit provided a reduced benefit. When testing factors that could potentially influence power to detect declines, we found that the power within sites was positively related to species abundance. Power was similar between biennial sampling (3 of 5 years) and annual sampling (5 of 5 years), suggesting a more cost-effective approach would be to sample every other year. We found that within most sites, detecting annual declines of 10% or less over a relatively short 5-year duration would be difficult. Hence, we recommend that salt marsh bird monitoring programs in the northeastern United States conduct two visits to each site per sampling year, include 15 or more sampling points per site (without confounding spatial independence), and conduct monitoring efforts every other year. This approach will maximize the efficacy of site-level monitoring of tidal marsh birds, which

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Abbreviations: CLRA, Clapper Rail; SALS, Saltmarsh Sparrow; SESP, Seaside Sparrow; TMO, Tidal Marsh Obligate; WILL, Willet.

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can aid in assessments of coastal wetland conservation and related habitat management efforts.

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1. Introduction

Tidal marshes are important, yet globally rare ecosystems that form the dominant transition zone between terrestrial and marine communities (Greenberg et al., 2006; Mcowen et al., 2017). This habitat provides vital ecosystem services that benefit humans both regionally and locally. Tidal marshes absorb energy from ocean storms, preserve shorelines, provide nutrients to marine food webs, and supply critical habitat for breeding and migratory birds (Barbier et al., 2011; Boerema et al., 2016; Wainger et al., 2017). Increasingly, tidal marshes are also providing critical risk reduction services that help mitigate widespread economic losses due to damage and recovery from major storm events along the northeast coast of the United States (Narayan et al., 2017). For example, within the past decade in the eastern United States, hurricanes Irene, Isaac, Sandy, Irma, and Harvery cost over USD 256 billion (NOAA National Centers for Environmental Information, 2020). For these reasons, continued monitoring of tidal marsh ecosystems and specialized communities and sentinel species that are sensitive to changes in habitat quality remains imperative.

As such, effective monitoring programs must be able to accurately quantify established metrics and use these metrics to periodically evaluate the ability to detect meaningful change in populations over time (Gibbs et al., 1998; Thompson et al., 1998; Urquhart and Kincaid, 1999; Larsen et al., 2001). Through the comparison among potential monitoring designs, we can systematically determine approaches that will maximize our power to detect changes in focal metrics and simultaneously minimize costs related to effort without sacrificing information quality (Caughlan and Oakley, 2001; Reynolds et al., 2011). Therefore, it is necessary to explore how the power to detect changes in population sizes over time is influenced by key attributes of monitoring designs such as survey methods, sample size, intervals between sampling occasions, and program duration (Lindenmayer and Likens, 2010; Thompson, 2004; Reynolds et al., 2016).

Within saltmarsh habitat, Neckles et al. (2013) has identified breeding bird abundance as a key response metric for the evaluation of habitat management actions that are now being used to assess the condition of salt marshes in the northeastern United States. Breeding bird species that depend on salt marshes are also among the highest conservation priorities in North America (Panjabi et al., 2017). Several species including the seaside sparrow (*Ammospiza maritimus*) and saltmarsh sparrow (*A. caudacuta*) are experiencing precipitous declines (Watts, 2016; Correll et al., 2017; Field et al., 2017; Roberts et al., 2019). Understanding how avian communities, and specifically, how representative focal species are responding to changes in saltmarsh habitat quality has provided pertinent information for long-term monitoring and conservation efforts (Klingbeil et al., 2018). Therefore, it remains important to monitor these populations. Not only to further support the conservation of tidal marsh-dependent species, but to maintain the continued assessment of the overall condition and status of tidal marshes in the northeastern United States.

We analyzed data from an existing extensive avian point count dataset from the northeastern United States, collected through the cooperation of academic, government, and non-government institutions (SHARP, 2017). The goal of our study was to evaluate and compare monitoring designs being actively considered by U.S. Fish & Wildlife Services' (USFWS) established salt marsh integrity (SMI) monitoring initiative that includes tidal marsh-dependent bird species as key monitoring metrics (Neckles et al., 2013). Selected focal species that nest almost exclusively in salt marshes in eastern North America, included the clapper rail (*Rallus crepitans*), the willet (*Tringa semipalmata*), the seaside sparrow, and the saltmarsh sparrow. We additionally included a composite measure of abundance for all four tidal marsh obligate (TMO) species within our analyses, as it is one of the established key metrics for salt marsh integrity evaluation (Neckles et al., 2013).

Our study was designed to support the evaluation of the USFWS' efforts to monitor salt marsh habitat dynamics in the northeastern United States throughout 22 refuges and refuge complexes within USFWS Region 5 (Neckles et al., 2013). To this end, we developed a suite of potential monitoring designs that reflected the specific management goals for tidal marsh habitat on USFWS National Wildlife Refuge (NWR) lands (e.g., see Neckles et al., 2019). For each monitoring design, we further examined how a suite of covariates that included the sample size, and the initial site-level species abundance influenced the statistical power to detect simulated population declines. Our study provides new and important information for optimizing monitoring designs for tidal marsh birds of conservation concern. This information will help ensure that monitoring efforts are logistically and economically efficient. Moreover, optimized monitoring designs will be effective for accurately measuring local-scale (e.g., within NWRs) population dynamics of tidal marsh bird species of conservation concern to support overall tidal marsh habitat conservation and management.

2. Materials and methods

2.1. Study area

We sampled bird abundance in tidal marsh habitat within 22 USFWS NWRs along the northeast coast of the United States (Fig. 1). Refuges and refuge complexes included (north to south): Moosehorn (MSH), Maine Coastal Islands (MCI), Rachel

Carson (RHC), Parker River (PKR), Monomoy (MNY), Sachuest Point (SPT), John H. Chafee (JHC), Ninigret (NGR), Stewart B. McKinney (SBM), Wertheim (WRT), Seatuck (STK), Lido Beach Wildlife Management Area (CLB), Edwin B. Forsythe (EBF), Supawana Meadows (SPN), Cape May (CPY), Bombay Hook (BMH), Prime Hook (PMH), Chincoteague (CHN), Wallops Island (WAL), Eastern Shore of Virginia (ESV), Fisherman Island (FSH), and Plum Tree Island (PTI; see Table 1 for details). Tidal marshes throughout our study area contain six major cover types defined by differing dominant vegetation communities, and varying tidal inundation regimes. The broad cover types include High marsh (flooded during extreme tides and dominated by *Spartina patens*, *Distichlis spicata*, and *Juncus gerardii*, as well as short form *Spartina alterniflora*), Low marsh (regularly flooded and dominated by *Spartina alterniflora*), Salt pools/pannes (largely bare areas; sparsely vegetated), Terrestrial border (very rarely flooded with common occurrence of *Typha angustifolia*, *Iva frutescens*, *Baccharis halimifolia*, *Solidago sempervirens*, *Scirpus robustus*, and *Spartina pectinate*), Phragmites (stands of the non-native invasive *Phragmites australis australis*), and Mudflats (frequently flooded non-vegetated exposed muddy areas; Correll et al., 2019).

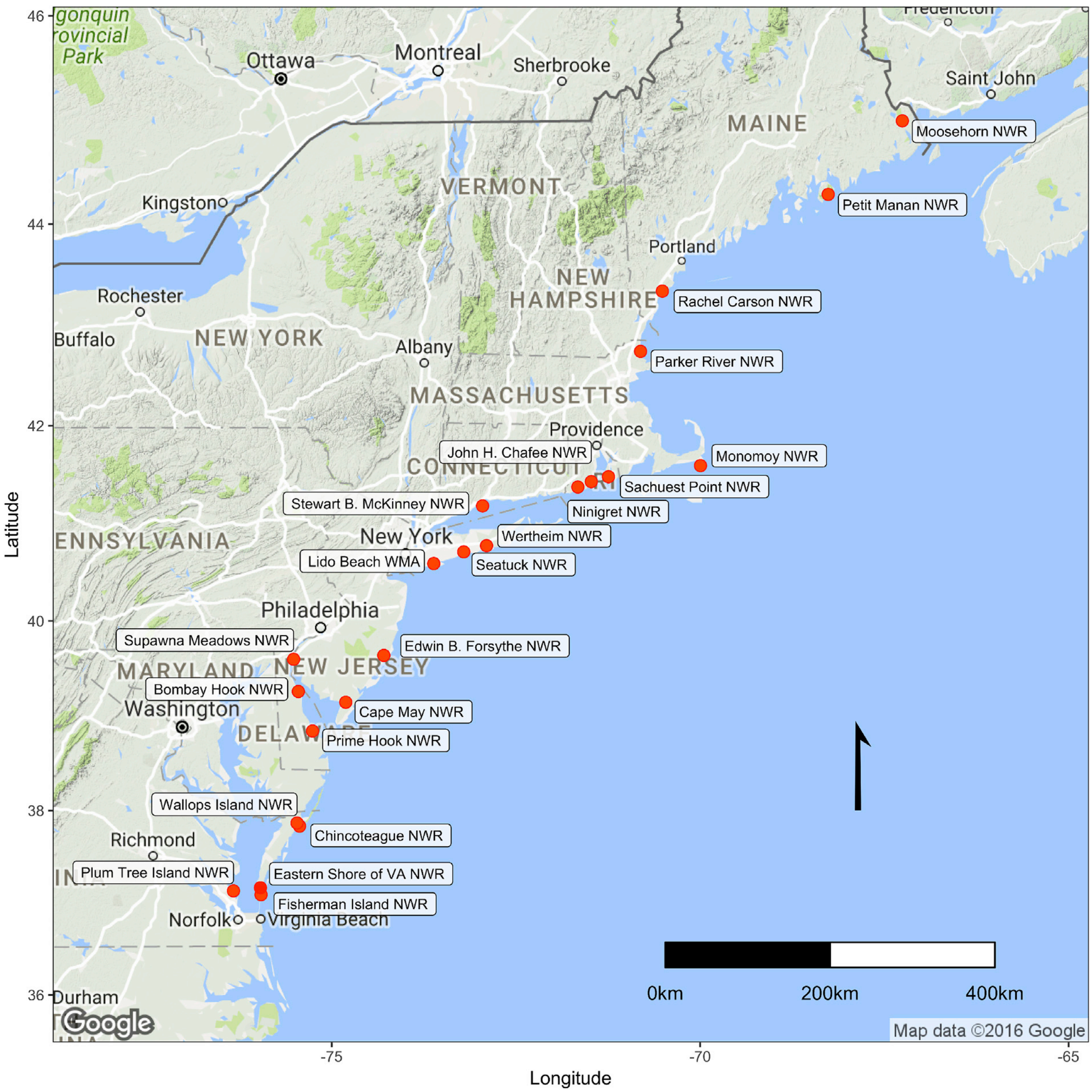

Fig. 1. Map of study area showing locations of 22 U.S. Fish and Wildlife National Wildlife Refuges along the northeastern coast of the United States, where Salt Marsh Integrity (SMI) sites ($n = 124$) and sampling points ($n = 1176$) were used to estimate abundance for focal tidal marsh avian species.

Table 1
List of 22 U.S. Fish and Wildlife Service National Wildlife Refuges (Region 5; ordered north to south) and corresponding 3-letter abbreviations, states, centroid coordinates, tidal marsh area (ha), number of designated sampling sites, and total number of sampling points where tidal marsh avian point count survey data were collected between 2011 and 2015.

National Wildlife Refuge	NWR code	State	Latitude	Longitude	Area (ha)	Num. of sites	Num. of points
Moosehorn	MSH	ME	−67.256175	45.000685	13.2	4	12
Petit Manan	MCI	ME	−68.262736	44.289876	30.2	2	12
Rachel Carson	RHC	ME	−70.513134	43.342809	786.4	20	145
Parker River	PKR	MA	−70.808889	42.745616	917.1	16	158
Monomoy	MNY	MA	−69.995920	41.595834	53.1	3	19
Sachuest Point	SPT	RI	−71.244551	41.482872	12.2	2	6
John H. Chafee	JHC	RI	−71.477794	41.432778	33.6	5	14
Ninigret	NGR	RI	−71.660435	41.378010	10.0	2	6
Stewart B. McKinney	SBM	CT	−72.953304	41.185438	129.3	2	18
Wertheim	WRT	NY	−72.899330	40.777906	165.7	3	35
Seatuck	STK	NY	−73.208885	40.713531	20.8	1	7
Lido Beach WMA	CLB	NY	−73.616127	40.593952	5.6	1	3
Edwin B. Forsythe	EBF	NJ	−74.293409	39.640889	12469.3	23	274
Supawna Meadows	SPM	NJ	−75.517476	39.600435	677.5	2	39
Cape May	CPY	NJ	−74.810426	39.149758	794.3	8	86
Bombay Hook	BMH	DE	−75.453444	39.262554	4586.9	8	115
Prime Hook	PMH	DE	−75.261142	38.846493	830.8	3	32
Chincoteague	CHN	VA	−75.437168	37.833659	1428.8	11	119
Wallops Island	WAL	VA	−75.471747	37.866659	71.8	1	10
Eastern Shore of VA	ESV	VA	−75.967976	37.170571	168.2	4	27
Fisherman Island	FSH	VA	−75.959512	37.095020	298.3	2	27
Plum Tree Island	PTI	VA	−76.334110	37.136325	958.7	1	12
				Total	24462.0	124	1176

2.2. Data collection

We collected data within 124 previously-established SMI sites (hereafter "sites") as part of the USFWS initiative to quantify salt marsh ecosystem integrity within NWRs throughout the study area (Neckles et al., 2013). Sites located within NWRs were delineated using available aerial imagery and represented areas of homogenous levels of disturbance or management applications. Among all of the sites, which were chosen based on marsh geomorphology and potential management actions, we selected a total of 1176 sampling locations (hereafter "points") to conduct tidal marsh avian surveys following Johnson et al. (2009) to achieve a spatially-balanced sample. This method used a 2-stage cluster sampling design and relied on generalized random-tessellation stratified (GRTS) sampling at both stages (Stevens and Olsen, 1999, 2003, 2004). In stage 1, we generated primary and secondary sampling hexagons using the 'spsurvey' package (Kincaid et al., 2011) in program R (R Core Team, 2010) by first selecting a subset of cells from a continent-wide grid of 40-km^2 hexagons that covered the tidal marshes from Maine to Virginia. Then in stage 2, we subsequently located 20 potential GRTS sampling locations (hereafter "points") within each of the previously selected hexagons (see Wiest et al., 2016 for details). To ensure spatial independence among points, each point was at least 400 m apart (Wiest et al., 2016).

Trained observers followed the North American Marsh Bird Monitoring Protocol (Conway, 2011) to conduct fixed-radius circular point count surveys at each of the points from 15 April through 31 July 2011–2015. During each annual season, observers visited points 1 to 3 times and conducted all surveys between 30 min before sunrise and 1100 h. At each survey location, observers recorded the number of unique individuals detected within corresponding distance bands (0–50 m, 51–100 m, and >100 m). During each survey, the time of detection (for each individual) was recorded within 1-min time intervals during an initial 5-min passive listening period and a subsequent period that included elicited detections using standardized playback recordings. However, for this study, we used only data from the 5-min passive listening period (Correll et al., 2016; Wiest and Shriver, 2016; Wiest et al., 2016). Observers also recorded information on survey covariates that included wind speed index, sky condition index, and weather conditions that were used to constrain the data we used in our analysis. For instance, we did not conduct surveys in high wind, sustained rain, or foggy weather conditions.

2.3. Abundance estimation

We estimated the abundance (i.e., the mean number of birds per point per site) for each species and the TMO composite. We constrained our analysis by using only data with detections within a 0 to 100-m radius, and we fit generalized multinomial N-mixture models (Royle, 2004; Chandler et al., 2011) with the gmultmix() function in the 'unmarked' package (Fiske and Chandler, 2011) in R (R Core Team, 2016). The hierarchical N-mixture model assumes population closure within each of the independent primary sampling occasions (in our case, years). The form of the generalized N-mixture model consists of three nested levels that describe both influence of the ecological process or state variable of population size and the observation process on the estimated abundance. The first level represents the latent state variable of population abundance and is modeled as a Poisson distribution: $M_i \sim \text{Poisson}(\lambda)$ where, M_i is the total number of individuals at point i and λ

represents the mean population size. The second level of the state model denotes the portion of the total population (N_{it}) at a given point i on occasion t that are available or present for sampling as $N_{it} \sim Binomial(M_i, \varphi_{it})$, where N_{it} is a subset of the total population size at a given point (M_i), and φ_{it} represents the probability that an individual within the total population is present during a survey, and hence, is available for detection at point i on occasion t. The binomial distribution used here uses Kendall et al. (1997) "completely random" temporary emigration model which assumes each individual with a population has a random probability of being present or absent, represented by φ and 1-φ, respectively. The third level consists of the observation process $\boldsymbol{y}_{it} \sim Multinomial(N_{it}, \boldsymbol{\pi}_{it})$, where $\boldsymbol{y}_{it}$ is a vector of newly-counted individuals detected within each given 1-min time interval over a 5-min duration at point i on occasion t. Multinomial cell observations ($\boldsymbol{y}_{it}$) are then conditional on both the total number of individuals available for sampling (N_{it}) and vector of detection probabilities ($\boldsymbol{\pi}$). The detection probability component ($\boldsymbol{\pi}$) of the observation process is modeled as a vector of multinomial cell probabilities. For example, for five 1-min time intervals, $\boldsymbol{\pi} = \{p, (1\text{-}p) \times p, (1\text{-}p)^2 \times p, (1\text{-}p)^3 \times p, (1\text{-}p)^4 \times p\}$, therefore, $\boldsymbol{\pi}_{it}$ represents the vector of detection probabilities for each 5-min removal sampling interval (Fiske and Chandler, 2011).

We first partitioned our data by NWR, where each NWR contains multiple sites, and then fit generalized multinomial N-mixture models described above. We included site to estimate the mean and variance of expected abundance among points for each site. For all models, we held the availability term in the model constant. To capture likely changes in species detection probability throughout the breeding season and to account for variation in weather conditions that may affect detectability, we included visit number (i.e., 1, 2, and 3) as a categorical variable within all models as an observation process covariate (Wiest and Shriver, 2016). We subsequently used these mean and variance estimates of abundance at each site as the initial conditions to simulate new point count data that represented declining population trends independently within each site.

2.4. Power analysis

To estimate the power to detect a population decline, we first generated 11,544 independent datasets of simulated point count data (i.e., the expected number of individuals at each hypothetical point and year for four species plus TMO). These simulated datasets were informed by the mean and variance of species abundances that we initially estimated at each site (see 2.3 Abundance estimation). We chose to model four annual rates of decline (i.e., 5%, 10%, 30%, or 50%), in accordance with the range of observed and potential population declines for the four species within our study area (Correll et al., 2016; Field et al., 2019; Roberts et al., 2019).

We estimated abundance from our simulated count data using a similar approach to mirror the hierarchical generalized N-mixture model used previously to estimate abundance from actual sampled count data (see above). Within the simulation analysis, initial abundance (i.e., abundance in year 1) was modeled as $M_{it} \sim \text{Poisson}(\lambda_{it})$ at time $t = 1$ (i.e., year 1) with the log-linear regression model: $\log(\lambda_{ij}) = B_0 + B_1[\text{site}_j]$, where, B_0 is the y-intercept and B_1 is the slope coefficient conditional for a given site j, which was treated as a random effect. We then estimated abundance of declining populations at each site in years 2 through 5 by applying each of the four fixed population decline rates (i.e., 5%, 10%, 30%, or 50%) to estimated annual abundances following Sollmann et al. (2015). As such, declining populations were modeled as $M_{it} \sim \text{Poisson}(M_{it\text{-}1} \times \gamma[\text{site}])$, where M_{it} is the estimated number of individuals at point i on occasion (year) t which is a function of the number of individuals present during the previous year (t-1), and γ represents the estimated trend, or annual rate of decline. To account for the observation process, we modeled the number of new individuals detected during each of the five 1-min sampling intervals at point i and time t as: $\boldsymbol{y}_{it} \sim \text{Binomial}(M_{it}, \boldsymbol{\pi}_{it})$, where $\boldsymbol{\pi}_{it}$ represents the conditional multinomial cell probabilities of detection at point i (Appendix A in Supplementary Materials). These detection probabilities were initialized using those previously estimated (see 2.3 Abundance Estimation) for each of the species independently, and for TMO. The model also incorporated the influence of timing of sampling within each year on the detection probability, captured by the categorical variable, visit, which was treated as a random effect and modeled as: $\text{logit}(p) = \alpha_0 + \alpha_1[\text{visit}_j]$ (see Appendix A in Supplementary Materials for full JAGS model). Since within the previous models used to estimate abundance we held availability constant in all cases, and since this process would vary for each of the species within our simulation analysis, we opted for a simpler model that omitted the availability component.

We independently estimated population trends (γ) for the simulated datasets that represented six potential monitoring scenarios for each species and TMO within each site over a 5-year monitoring duration. Monitoring designs differed in the periodicity of primary sampling occasions (i.e., annual or biennial) and in the number of within-season visits to each point (i.e., 1, 2, or 3). In the annual monitoring scenario, we used all 5 years of simulated count data, and in the biennial monitoring scenario, used simulated count data from years 1, 3, and 5. Each of the monitoring scenarios were run using count data with differing simulated annual population decline rates (5%, 10%, 30%, or 50%). All models were fit within a Bayesian framework using JAGS (version 4.3.0; Plummer, 2003) and 'rjags' (version 3; Plummer, 2013) in program R (R Core Team, 2016), and were run with three MCMC chains for 30,000 iterations, a burn-in of 10,000 iterations, and posterior distributions were thinned by every 20th iteration. We evaluated convergence of models with Gelman-Rubin statistics, none of which exceeded 1.2 (Gelman et al., 2014). We estimated power by simulating each scenario 100 times, and then tallied the number of times model-estimated decline rates were significant, defined as 95% BCIs not overlapping 1 (Sollmann et al., 2015). We acknowledge that our choice of a using simpler model (e.g., without specifically modeling the availability of individuals for detection), could lead to an increase in parameter precision, and hence, increased power to detect declines. However, using our count data, we did compare mean and variance estimates of abundance for each of the species using a simpler removal model and the model where we held availability constant, and found no discernible differences providing us with confidence that simulation-based estimates of power are not artificially inflated as a function of using a simpler modeling approach. The proportion of significant declines that were detected from 100 iterations for each scenario are interpreted as power estimates (a monitoring scenario performance metric). We then compared the relative performance of each monitoring design for each species and TMO based on estimated power results.

2.5. Evaluation of monitoring design scenarios

We evaluated broad-scale geographic patterns in the power to detect population declines through visual inspection of power among sites for all scenarios and species by ranking sites from north to south by decreasing latitude. To further compare generalizable patterns among potential monitoring scenarios throughout the study area, we calculated the proportion of sites that had an adequate power of $\geq$0.75, which we define here within our study, as the minimum required power to detect a decline that would be meaningful to USFWS scientists to develop and apply mitigative management strategies. We also compared distributions of power estimates among scenarios for each species among annual decline rates. Finally, we fit logistic regression models for each species independently using the glm() function from the ‘stats (version 3.6.1)’ R package (R Core Team, 2016) with the family parameter = “binomial(link = “logit”)” which incorporated the power at each site as a continuous response variable. Within each of the models, we included Scenario × Decline × Site × nVisits × nPoints as a full-factorial interaction term of predictor variables. We then used this model to predict the minimum number of required sampling points that would be required within a site to achieve at least a power of 0.75. All analyses were conducted using program R (version 3.3.2; R Core Team, 2016). Furthermore, our determination of an optimal monitoring design included considering inherent trade-offs between benefits of increasing power to detect lower annual rates of decline and associated monetary and logistical costs stemming from increased monitoring efforts. We also sought to find a monitoring design that would be effective in detecting biologically-relevant declines for each of the four focal species and TMO in accordance with monitoring objectives currently being used by USFWS.

3. Results

3.1. Initial abundance estimates

The total number of sites where each of the four species and TMO were detected were as follows: willets ($n = 112$ sites), saltmarsh sparrows ($n = 109$ sites), seaside sparrows ($n = 71$ sites), clapper rails ($n = 66$ sites), and TMO ($n = 124$ sites). We estimated site-level abundance (i.e., number of individuals per point; mean ± SE) for clapper rails (1.01 ± 0.19), willets (1.34 ± 0.11), saltmarsh sparrows (1.96 ± 0.28), seaside sparrows (2.20 ± 0.31) and TMO (3.92 ± 0.30; Table 2). Additionally, geographic patterns of site-level abundance differed among sites and species (Fig. 2).

3.2. Power analysis results

In general, distributions of power estimates among monitoring design scenarios with annual and biennial sampling over a 5-year monitoring period were similar (Fig. 4, Supplemental Materials; Appendix B). We also found that, in general, the proportion of sites with a power $\geq$0.75 to detect population trends increased as the number of within-year repeated visits increased from one visit to either two or three visits (the latter two of which were similar; Fig. 3). The number of sampling points within a site was also positively related to the power to detect annual declines among all focal species and TMO.

We were able to detect population trends resulting from either 50% or 30% annual population declines for all of the focal species and TMO with adequate power under all monitoring scenarios (Figs. 3 and 4). However, we did find that overall power to detect declines differed among species, particularly when comparing power estimates for willets and clapper rails versus seaside and saltmarsh sparrows at 5% and 10% annual decline rates (Fig. 4). For example, we were able to detect 10% annual declines for TMO, saltmarsh sparrows, and seaside sparrows under all monitoring design scenarios, but at fewer sites (Fig. 4). Whereas for clapper rails under a 10% annual decline, we were able to detect site-level declines only when at least two repeated visits per sampling year occurred (Fig. 4). We detected a 10% annual decline for willets with adequate power ($\geq$0.75),

Table 2
Summary statistics describing initial abundance estimates (individuals per sampling point; $n = 1176$ points) including mean, SE, coefficient of variation (CV), minimum (Min), maximum (Max), and proportion of sites where species were detected for each monitoring metric ($n = 124$ sites). Species common names (Species) are shown.

Species	Mean	SE	CV	Min	Max	Proportion of sites detected
Tidal Marsh Obligate	3.92	0.30	0.86	<0.1	13.73	1.00
Willet	1.34	0.11	0.87	<0.1	5.79	0.90
Saltmarsh sparrow	1.96	0.28	1.44	<0.1	13.39	0.88
Seaside sparrow	2.20	0.31	1.28	<0.1	11.40	0.57
Clapper rail	1.01	0.19	1.59	<0.1	11.02	0.53

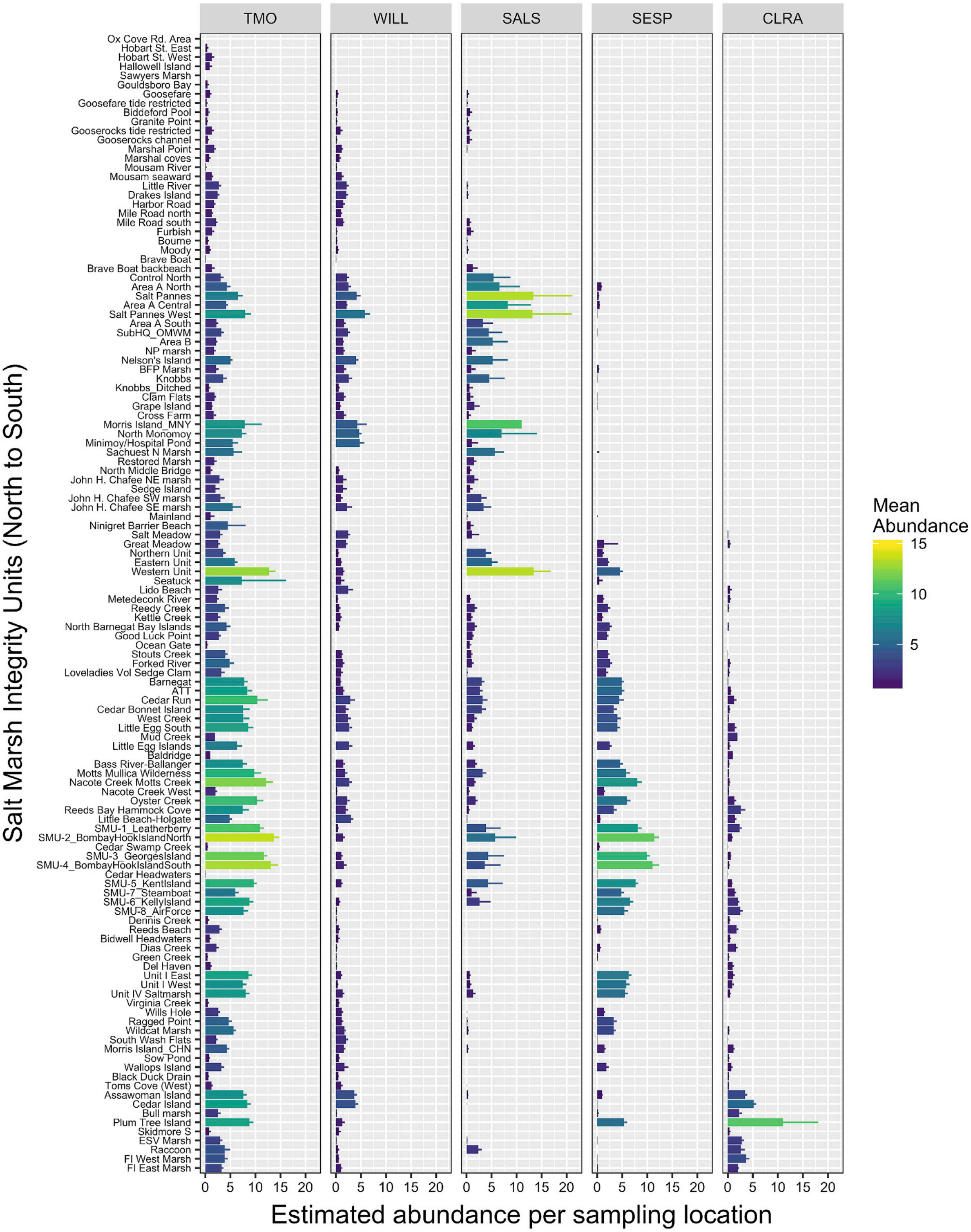

Fig. 2. Estimated site-level species abundance (mean ± SE) per monitoring point during 2011–2015 for the tidal marsh obligate (TMO), the willet (WILL), the saltmarsh sparrow (SALS), the seaside sparrow (SESP), and the clapper rail (CLRA) at 124 salt marsh integrity (SMI) sites ordered from north to south in the northeastern USA.

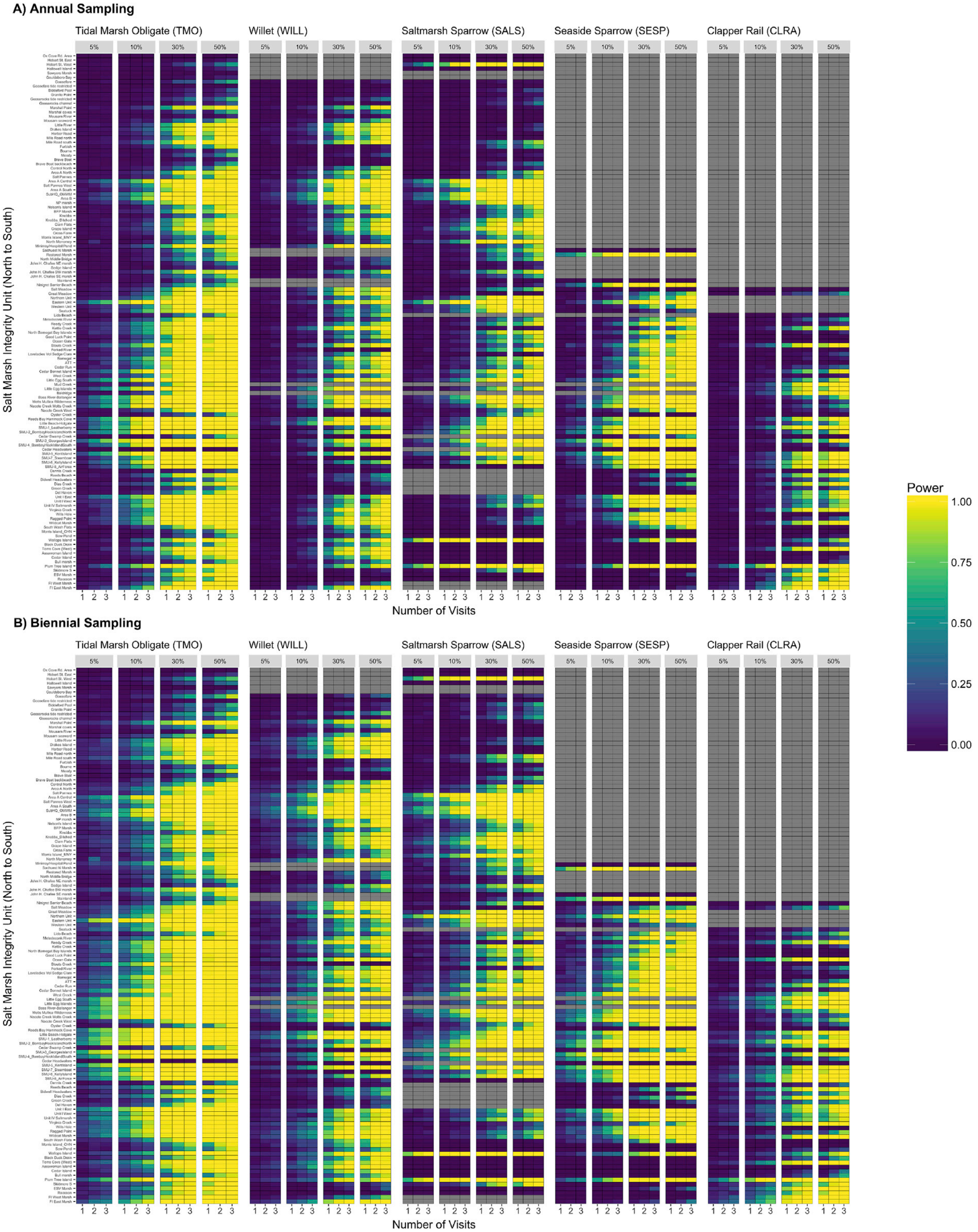

Fig. 3. Power estimates for 124 salt marsh integrity (SMI) sites under A) annual and B) biennial sampling regimes with either 1, 2, or 3 visits per sampling year. Power estimates are shown under 5%, 10%, 30%, and 50% annual declines for tidal marsh obligates, willets, saltmarsh sparrows, seaside sparrows, and clapper rails. Gray-shaded cells are NAs where species were not detected within sites.

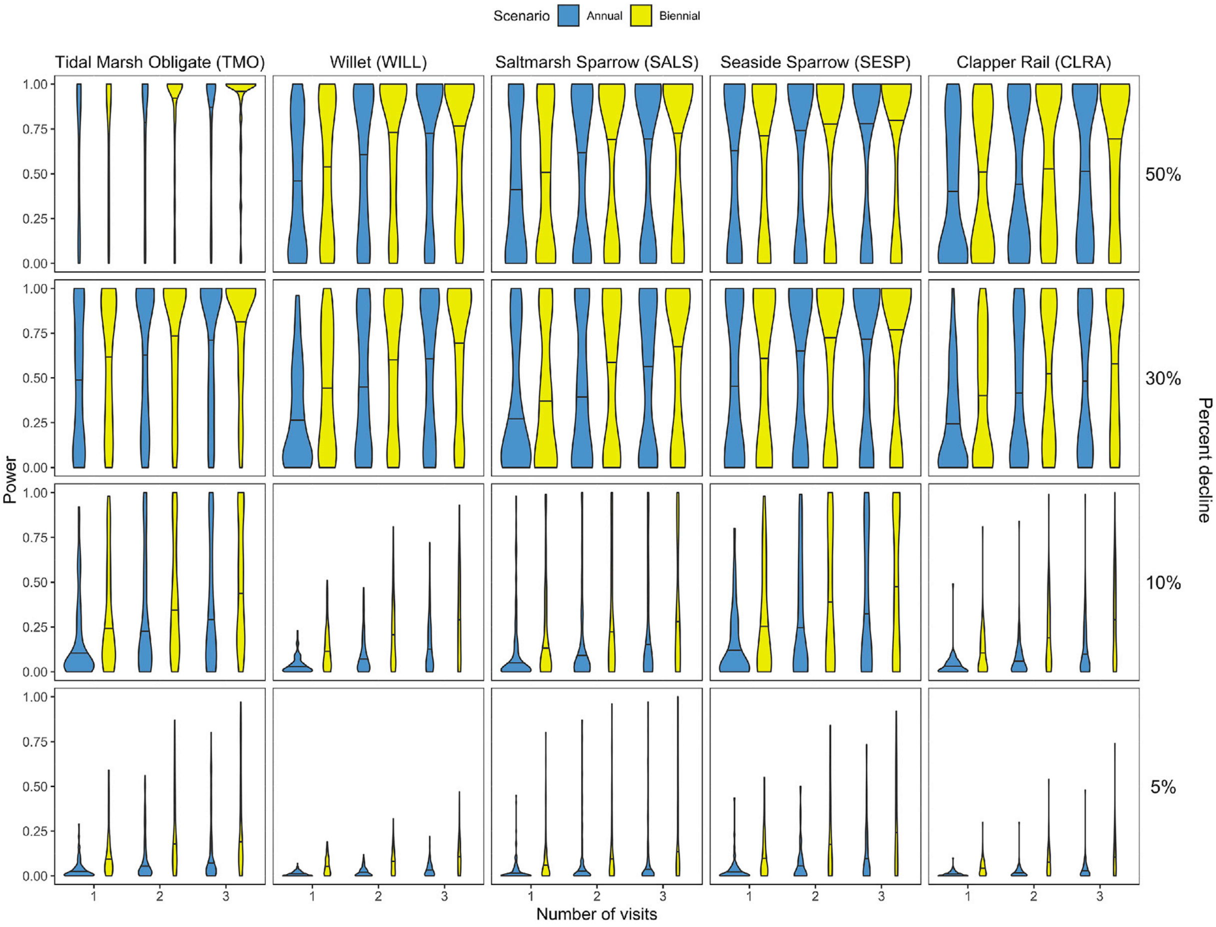

Fig. 4. Distributions of power estimates among six monitoring design scenarios for detecting 5%, 10%, 30%, and 50% annual population decline rates. Monitoring designs with annual (blue) and biennial (yellow) sampling and 1, 2, or 3 repeated visits are shown for tidal marsh obligates, willets, saltmarsh sparrows, seaside sparrows, and clapper rails. Black lines indicate median values. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

but only with two or three repeated visits per sampling year (Fig. 4). For saltmarsh sparrows, seaside sparrows, and TMO we were able to detect a 5% annual decline, but only at very few sites (see Figs. 3 and 4).

To detect a 30% or 50% annual decline for willets, saltmarsh sparrows, seaside sparrows, and TMO, under any of the monitoring scenarios, a minimum of 15 sampling points per site would be required. However, to detect a 30% or 50% annual decline for clapper rails would require at least 17 sampling points per site, when visited a minimum of two times each season (Fig. 5). For willets, saltmarsh sparrows, and seaside sparrows, we were able to detect a ≥30% annual decline at sites having 15 or more points with a minimum of two visits per season. However, to detect a 10% decline under that same monitoring design for seaside and saltmarsh sparrows, sites would require 20 or more points to achieve adequate power (Fig. 5). Whereas for TMO, we detected a ≥10% annual decline at sites with 15 or more sampling points, and at least two repeated within-season visits (Fig. 5).

4. Conclusions

Evaluating the effectiveness of monitoring programs to detect meaningful population trends continues to be a critical component for ecosystem and wildlife management and conservation. In our simulation-based study of tidal marsh birds in the northeastern United States, we compared the ability of different monitoring designs using a time-removal sampling framework, to detect annual population declines at local scales (e.g., a tidal marsh site located within a NWR), to help inform local-scale habitat management decisions. Our results will help determine site-specific guidelines (e.g., number of sampling locations) that are required to achieve effective monitoring program outcomes. Due to our study's objective of providing more granular site-level information to improve management efforts at local spatial scales, it is unsurprising that statistical power to detect short-term declines are diminished, in general. However, we note that despite differences in the scope, objective, and analytical approach of the current study, our findings that detection of declining trends of focal tidal marsh species are

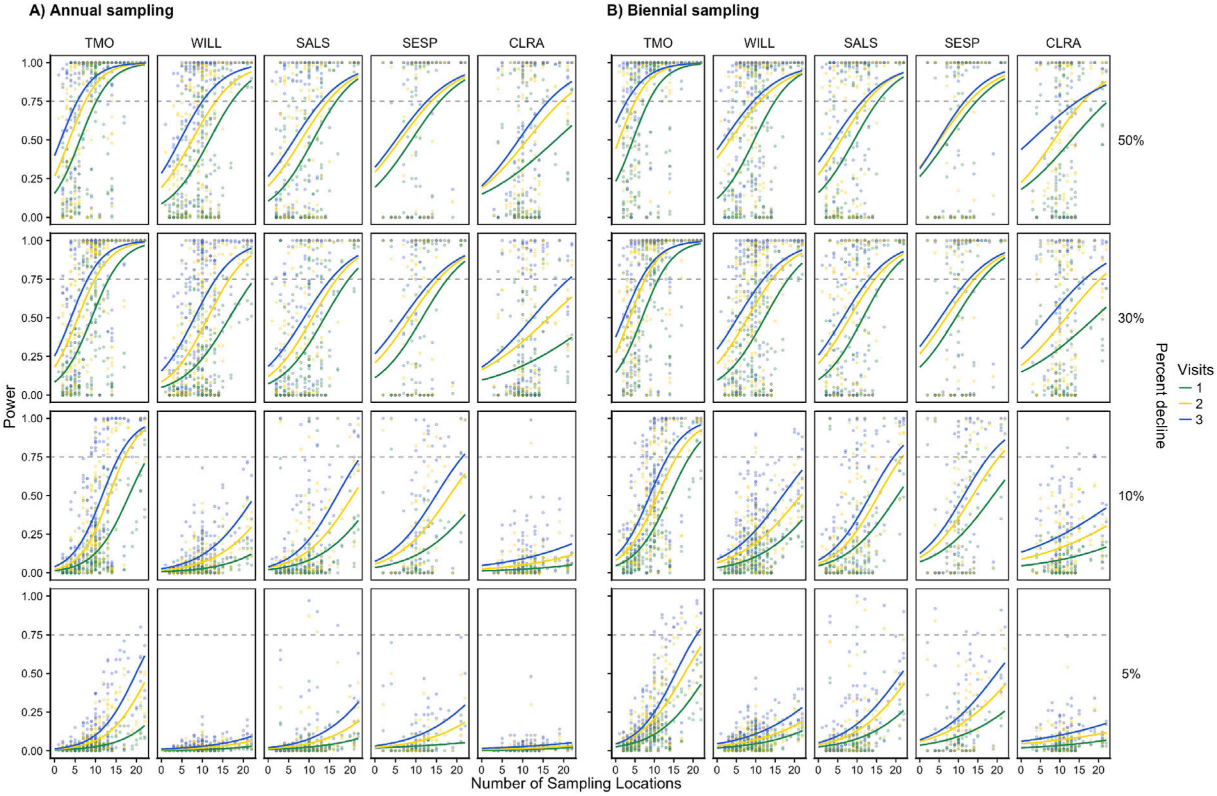

Fig. 5. Logistic regression of mean site-level power estimates and the number of sampling points. The power to detect 5%, 10%, 30%, and 50% annual decline rates for A) annual and B) biennial monitoring scenarios with either 1, 2, or 3 visits is shown for the tidal marsh obligate (TMO), the willet (WILL), the saltmarsh sparrow (SALS), the seaside sparrow (SESP), and the clapper rail (CLRA).

achievable under optimized monitoring designs complement the results from multiple recent studies that provide vital information at more regional scales to inform more generalized species conservation and ecosystem management goals (Field et al., 2019; Roberts et al., 2019; Wiest et al., 2019). Based on our findings, we recommend conducting a minimum of two repeated visits per season at each survey point, and sampling biennially. Under this sampling design, using a time-removal sampling protocol is required in order to achieve results supported by our study. This design will enable a logistically and cost-effective monitoring program that uses the least field effort to achieve the greatest power to detect annual declines of 30% or greater at specific sites throughout the northeastern United States (e.g., tidal marshes within state- and federally-managed lands). Additionally, to improve the power to detect site-level trends we suggest including 15 or more sampling points per site, where feasible without violating constraints arising from a site's total area and the ability to maintain spatial independence among points.

The importance of evaluating the effect of differing intervals between primary sampling periods on the power to detect changes in population size has been previously demonstrated (Taylor and Gerrodette, 1993). This, in turn, can lead to significant variation in the allocation of effort and cost, and ultimately, feasibility of implementing successful monitoring programs. Our results from comparing power estimates resulting from different monitoring periodicities indicated that biennial surveys are as good as annual surveys over a 5-year monitoring period. In this way, biennial sampling is able to balance trade-offs between the cost of sampling effort and the power to detect population trends. While similar patterns have been described in other monitoring design studies (Gerrodette, 1987; Wilson et al., 1999), these will likely only occur in situations with consistent log-linear positive or negative trends. However, we are aware that the possibility of non-linear population declines should also be considered, and may be particularly important for detecting exponential declines of species of conservation concern in the future.

Similarity in the ability to detect trends between monitoring designs using time-removal sampling methods with repeated visits to model abundance with either two or three within-season repeated visits suggests that increasing sampling effort beyond two visits each season may not be worthwhile. Wiest and Shriver (2016) explored how within-season survey frequency (i.e., repeated visits), using data that included up to 8 repeated visits within a sampling year, influenced abundance estimates, detection probabilities, and variance estimates, and found that saltmarsh sparrows had the lowest coefficients of variation for abundance under a 2-visit scenario. In another study, Field et al. (2016) found that the precision of abundance estimates of saltmarsh sparrows in Connecticut were not improved by increasing repeated visits. We furthermore suggest conducting two repeated visits to each point per sampling year since none of the focal species in our study are considered “rare”, which is in alignment with guidance from previous research on optimal allocation of survey efforts (Thompson et al., 1998; MacKenzie and Royle, 2005), and estimating abundance of species that exhibit heterogeneity in detection probability among sampling locations (Royle and Nichols, 2003).

One of the strengths that our large-scale study takes advantage of, is the spatially-balanced survey design (Wiest and Shriver, 2016), resulting in the wide breadth of regional coverage (from Maine to Virginia; Fig. 1). Over this geographic region, we observed wide variation in abundance estimates at sites for seaside sparrows, clapper rails, and willets (Fig. 2). This allowed us to explore how metrics important for monitoring design optimization, such as the number of sampling points, can influence the power to detect population declines. For example, for saltmarsh and seaside sparrows, greater than 20 points per site would enable detection of a 10% annual decline under a biennial sampling design with two repeated visits per season (see Fig. 5). The same was true for TMO when there were greater than 15 sampling points per site. Of course, the number of sampling points per site may be restricted by the extent of habitat area available, and other logistical constraints (e.g., effort and budgetary). Moreover, in situations where greater than 20 points are already established, and power to detect declines is ≥ 0.75, a desired strategy would be to redistribute “excess” points (i.e., sampling effort) to sites that are currently underrepresented. For clapper rails and willets in particular, as well as the other focal species, extending the overall monitoring period beyond 5 years will undoubtedly improve the ability of this monitoring program to effectively detect population declines.

Our results are complemented by findings from a previous study that examined how a focal species approach can be a useful and cost-effective method for prioritizing the conservation of habitat for tidal marsh specialist birds (Klingbeil et al., 2018). Using population density estimates from within our study area (Wiest et al. 2016, 2019), Klingbeil et al. (2018) demonstrated that from a regional perspective, protection of habitat for the saltmarsh sparrow, in this case acting as an umbrella species, should effectively provide protection for other tidal marsh specialist breeding birds. Hence, inference made from regional-scale population estimates of saltmarsh sparrows can adequately inform conservation decisions for other tidal marsh species (Klingbeil et al., 2018). In our study, power estimates of saltmarsh sparrows were also similar to willets and seaside sparrows (see Figs. 3 and 4), implying that an optimal monitoring design to detect declines in saltmarsh sparrows will also be useful to detect declines for these focal species.

We have also demonstrated how by using a composite metric (i.e., TMO) of the four focal species under the recommended monitoring design, we were able to detect meaningful declines in a 5-year period. This supports the idea that monitoring marsh bird community dynamics or using a guild-based approach is also a valuable way to asses changes in habitat quality that would be representative of tidal marsh species. Similarly, Shriver et al. (2004) demonstrated how marsh bird community diversity is linked with salt marsh habitat quality within a landscape context. Our methodological approach further highlights how data collected under an optimal monitoring design can offer flexibility in modeling single species or focal guilds, while retaining the ability to use community-level diversity metrics for future analyses at multiple spatial scales to support conservation and habitat management objectives.

Continuing to closely monitor indicator species that can provide insight into the health and function of tidal marsh ecosystems remains a necessity given increasing anthropogenic threats to coastal areas. Thus, improving monitoring efficacy for tidal marsh specialist birds is important and will provide better information for species conservation and ecosystem management decisions. Recent evidence, also using data from this study (SHARP, 2017), has suggested that coastal specialist species can show a high degree of resilience (e.g., recovery from acute population declines in as little as 20 years due to extreme disturbance events like hurricanes; Field et al., 2019). This is reassuring given projected increases in the frequency and overall energy of extreme storm events (AghaKouchak et al., 2020). However, for species of particular conservation concern, such as the saltmarsh sparrow, recent population viability analyses using a portion of data from our study (SHARP, 2017) suggest that within as little 20–25 years, saltmarsh sparrows may experience local extinctions in coastal New Jersey, which is a core part of their breeding range in the United States (Roberts et al., 2019). Therefore, it is timely and important that adaptive monitoring programs be implemented to estimate tidal marsh ecosystem health and function, optimize conservation decision-making, and evaluate the success of tidal marsh restoration and management to help prevent potential local extinctions. Here, we provide local-scale (i.e., site-specific) estimates for tidal marsh species abundance, and describe factors that can influence the power to detect biologically-meaningful population declines under alternative monitoring design scenarios being actively considered by USFWS. These findings can help enhance our ability to assess how tidal marsh specialist birds are responding to ecosystem dynamics and specific management actions. From a conservation perspective, reducing the time to detecting meaningful population declines will be paramount for managing tidal marsh ecosystems that are differentially affected by the burgeoning negative effects of climate change, sea-level rise, and encroachment of human development in coastal areas. In addition to our methodological recommendations for effective local-scale monitoring of tidal marsh birds in the northeastern United States, we advocate for continuing efforts to evaluate monitoring efficacy in an adaptive monitoring framework to ensure that current and future management objectives can be readily identified, prioritized, and implemented in reasonable timeframes.

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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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gecco.2020.e01128.

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