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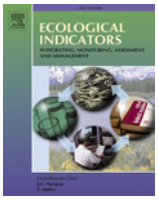

Leveraging local wildlife surveys for robust occupancy trend estimation

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ABSTRACT

Natural resource agencies are frequently tasked with monitoring populations of at-risk species to ensure management activities do not negatively affect the viability of wildlife populations. Typically, these monitoring efforts evaluate trends in a population's abundance, occupancy, or geographic distribution. Often, surveys provide local information, but results are generally not incorporated into broad-scale monitoring efforts that focus on range-wide population changes due to their variable nature in both spatial extent and effort. We investigated whether aggregating these local (hereafter "variable") surveys can generate enough statistical power to estimate broad-scale population trends using simulations of declining populations of fishers (*Pekania pennati*) over a 10-year time horizon. Our simulations included three population sizes which we refer to as abundant, common, and rare (N_0 = 700, 350, and 100 individuals, respectively) with each declining at a rapid and moderate pace (λ = 0.933, and 0.977, respectively). For each population, we simulated variable surveys using an occupancy framework to subsample the population with parameters that mimic combining multiple independent monitoring efforts which vary annually in location, and effort. Regardless of spatial consistency of annual sampling, there was minimal variation in statistical power under both high and low detection probability simulations. However, when sampling effort varied each year, statistical power was lower for most populations and sampling scenarios when compared to consistent sampling effort unless some baseline level of sampling effort was reliably achieved in all years. In many cases, adding low-level consistent baseline sampling to variable surveys resulted in statistical power close to that of consistent sampling efforts. Our results suggest statistical power is driven by annual consistency in the proportion of landscape sampled rather than spatial consistency in sampling locations. This result indicates that current variable surveys could be leveraged and combined to detect population declines for at-risk species at broad-scales if a baseline proportion of landscape is robustly sampled. The level of baseline sampling is highly dependent on population size and magnitudes of population change. In simulations with a common or abundant population experiencing a rapid decline, a baseline survey effort of at least 5% of the landscape in combination with variable surveys resulted in statistical power consistently above the standard threshold of 0.80 for occupancy monitoring. Leveraging existing local efforts to achieve high detection probability and baseline sampling would reduce financial and logistical burdens of broad-scale wildlife monitoring efforts.

1. Introduction

Recent widespread habitat loss resulting from climate change and human disturbances has raised concerns about the viability of many wildlife populations, warranting expanding monitoring efforts (Butchart et al., 2010; Nimmo et al., 2021; Tilman et al., 2017). Typically, wildlife monitoring programs are used to detect declines in species and identify when and where conservation efforts are needed (Lindenmayer and Likens, 2010; Nichols and Williams, 2006). However, documenting these population declines can be particularly challenging for at-risk species that are elusive, cryptic, and sparse (Emmet et al., 2021).

Detecting declines in populations of at-risk species generally requires

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intensive monitoring efforts across broad temporal and spatial scales (Field et al., 2007; Mulder and Palmer, 1999; Schwartz et al., 2015). To cover these broad scales, collaborative monitoring frameworks have become increasingly prevalent, for example, the North American Bat Monitoring Program (NABAT), the European Observatory of Wildlife (EOW), and eBIRD from the Cornell Lab of Ornithology (Beaudrot et al., 2016; ENETWILD-consortium et al., 2023; Jones, 2011; Keller et al., 2008; Loeb et al., 2015). The trend toward collaboration for monitoring species is also evident in land management agencies. The National Park Service of the United States developed a Natural Resource Challenge in 2000 which helped design long-term ecological monitoring programs that allow for evaluation of the status and trends of important park resources across 63 US National Parks (Fancy and Bennetts, 2012). Similarly, the United States Forest Service's (USFS) 2012 Forest Planning Rule provides recommendations to develop joint monitoring programs across 96.5 million hectares of National Forest to increase efficiency of wildlife monitoring (Schultz et al., 2013; U.S. Forest Service, 2012). A collaborative framework leverages multiple agencies throughout a species' range, providing a standard survey protocol and sampling locations and then compiling resulting data to assess broad-scale population metrics (Reichert et al., 2021; Rovero and Ahumada, 2017; Steenweg et al., 2016). Although robust, collaborative programs require extensive effort and funding to initiate and maintain, particularly when they require distinct sampling methods. In addition, managers and agencies are also required to conduct local surveys over short time intervals to inform site-specific environmental planning efforts with little contribution to broad-scale population trend assessments (Cash and Moser, 2000; Ellis et al., 2014; Fleischman et al., 2020; Ruggiero et al., 1994; Schultz, 2010; Schultz et al., 2019; Wiens, 1989). Across a species' range, there may be dozens of these disjunct local efforts from a variety of agencies and projects ranging from federally mandated monitoring under the 1970 National Environmental Policy Act (42 U.S.C. §§ 4321 *et seq.*) to monitoring programs run by state agencies or non-governmental organizations (NGOs; Stern et al., 2010). Among these 'variable surveys', which are generally short-term and local, there is little coordination, resulting in wide variation in annual sampling location and effort as well as in sampling protocols. Broad-scale collaborative monitoring efforts rarely employ existing variable surveys due to disparities in sampling protocols and effort despite their perpetual existence. Yet there is some evidence that aggregation of variable surveys may strengthen abundance, space use, and occupancy estimates (Gervasi et al. 2024; Tenan et al., 2017; van Strien et al., 2013).

Occupancy, the proportion of an area occupied by a species, is a cost-effective and commonly used metric for wildlife population monitoring (Devarajan et al., 2020; Joseph et al., 2006). It requires only detection/non-detection data across the sampling area rather than counts of individuals as required for other metrics such as abundance (MacKenzie and Nichols, 2004). Researchers have used the relationship between occupancy, spatial distribution, and abundance to conduct more robust population monitoring (Gaston et al., 2000; Holt et al., 2002; Linden et al., 2017; Sells et al., 2022; Stauffer et al., 2021; Steen et al., 2023). Yet, how occupancy can inform species abundance trends greatly relies on both temporal and spatial parameters of sampling scales and characteristics of the species of interest (Efford and Dawson, 2012; Ellis et al., 2014; Freckleton et al., 2005; He and Gaston, 2000; Steenweg et al., 2018). The ability of a monitoring project to detect changes in abundance through occupancy data is typically assessed through a power analysis involving simulated populations and survey frameworks (Ellis et al., 2014; Field et al., 2005; Rhodes et al., 2006). These power analyses evaluate competing sampling designs to determine whether a population change can be detected under each design (Ellis et al., 2014; Guillera-Arroita and Lahoz-Monfort, 2012; Southwell et al., 2019; Tucker et al., 2021). Comprehensive and open-source code packages such as `rSPACE` (Ellis et al., 2015) and `DynOccuPow` (Banner et al., 2019) were developed to conduct these analyses efficiently, allowing agencies and managers to design effective and practical monitoring programs. However, these programs focus on systematic survey efforts and cannot accurately assess statistical strength of variable surveys.

We built on existing code packages and used simulations to determine statistical strength of variable surveys to assess broad-scale population trends for rare species. It is generally assumed that variable surveys have reduced statistical power to detect population trends, yet conditions under which they could reliably detect such trends are unknown. Here, we conduct a spatially based power analysis for variable surveys on a simulated population of fishers (*Pekania pennanti*) in the Rocky Mountains of northern Idaho and western Montana, USA. As a 'Sensitive Species' in numerous National Forests, USFS is legally mandated to monitor populations of fishers under the 2012 Forest Planning Rule (Schultz et al., 2013; U.S. Forest Service, 2012). These existing monitoring efforts by USFS, as well as others conducted by state agencies, for fishers throughout the western US serve as a prime example of variable surveys that could be integrated into a collaborative monitoring effort. We simulated a series of sampling frameworks that vary spatially, where locations of sampling are inconsistent among years (hereafter 'spatial variability'), and in intensity of sampling effort each year (hereafter 'effort variability'). While we focused on fishers for this analysis, we expect these results could be implemented on a wide array of species with similar traits, especially mid-sized carnivores such as red fox (*Vulpes vulpes*), American and Pacific marten (*Martes americana, Martes caurina*), wolverine (*Gulo gulo*), and Canada lynx (*Lynx canadensis*).

2. Materials and methods

2.1. Simulation process

We conducted a spatially based power analysis for monitoring a Distinct Population Segment (DPS) of fishers in the Rocky Mountains of northern Idaho and western Montana, USA, using simulations built in a modified version of the program `rSPACE` (Ellis et al., 2015; Fish and Wildlife Service, 2017). This DPS has been considered for listing under the Endangered Species Act multiple times since 1994 and represents a discrete subpopulation that is significant to the species as a whole (Fish and Wildlife Service, 2017, 2011, 2010). We used simulations of six population parameter sets to represent fishers in the Rocky Mountains (Table 1).

For all populations, we used plausible movement parameters based on home range estimates for fishers in the study area (Table 1) and a habitat suitability layer to randomly place simulated individuals across the study area (N_0 = 700, 350, 100; Fig. 1B; Ellis et al., 2015; Olson et al., 2014; Sauder and Rachlow, 2014). The habitat suitability layer was developed by Olson et al. (2014) and reflects fisher distribution throughout northern Idaho and western Montana, USA. Individual home range centers had a minimum habitat suitability value of 0.1, but otherwise placement was not weighted by habitat suitability due to computational limitations (Table 1; Olson et al., 2014). Males and females were simulated in equal proportions to represent sexual dimorphism in movement patterns and home range sizes (Table 1). For males, home range centers were spaced a minimum of 6.69 km apart with a home range radius of 5.35 km, allowing for a large amount of overlap (Fig. 1B; Table 1). In contrast, female home range centers were spaced a minimum of 6.58 km apart with a home range radius of 3.76 km (Fig. 1B; Table 1). We based these home range size and overlap values for males and females on previous analyses of fisher home ranges in both the Rocky Mountains and the Sierra Nevada of California, USA (Olson et al., 2014; Powell and Zielinski, 1994; Sauder and Rachlow, 2014; Weir et al., 2009; Zielinski et al., 2004). We created an individualized bivariate normal movement distribution for each individual, weighted by the underlying habitat suitability model, and truncated to only include the 95% quantile (Table 1; Ellis et al., 2015). These movement distributions were then aggregated to create a raster representing probability of use of at least one individual across the study area for the

Table 1
Population, movement, and sampling parameters for each population set with a brief description. Parameter values in bold are not consistent between population sets. Further information about parameter definitions can also be found in Ellis et al. (2015).

Parameter	Population Sets					
	Abundant-50 %	**Abundant-20 %**	**Common-50 %**	**Common-20 %**	**Rare-50 %**	**Rare-20 %**
Starting population size	**700**	**700**	**350**	**350**	**100**	**100**
Simulated population growth rate	**0.933**	**0.977**	**0.933**	**0.977**	**0.933**	**0.977**
Total number of years, including the initial year			11			
Sex ratio of males to females			0.5, 0.5			
Minimum habitat suitability value for home range centers to be located			0.1			
Distance between home range centers for males and females, respectively			6.69, 6.58 km			
Approximate home range radius for males and females, respectively			5.35, 3.76 km			
Proportion of movement within home range radius for males and females, respectively			0.99, 0.99			
Proportion of movement distribution to include for males and females, respectively			0.95, 0.95			
Minimum proportion of the sampling cell that must be at or above the habitat cutoff to be considered for sampling			0.5			
Total area covered by each sampling cell			56 km^2			
Total number of simulated populations with these parameters			100			

initial population (Ellis et al., 2015).

Our power analysis focused on the ability of occupancy monitoring to detect population declines. Recognizing that rates of population declines can greatly affect a monitoring program's statistical power, we simulated both moderate and rapid abundance declines under an exponential growth model ($\bar{\lambda} = 0.977, 0.933$; corresponding to a 20% and 50% decline in abundance over 10 years). We designed our framework to simulate populations over time, with each time step being defined by the turnover rate of the species. In our simulations, each time step represents one year. Declines were simulated by randomly removing the number of individuals which would achieve the respective value of λ between each year (Ellis et al., 2015). Remaining individuals' movement distributions were then re-aggregated to create a "probability of use of at least one individual" raster for that year (Ellis et al., 2015). We repeated this process for ten subsequent years. The combinations of initial abundances (N_0) and rates of decline ($\bar{\lambda}$) resulted in six simulated population sets: Abundant with Moderate Decline (Abundant-20%; $N_0 = 700; \bar{\lambda} = 0.977$), Abundant with Rapid Decline (Abundant-50%; $N_0 = 700; \bar{\lambda} = 0.933$), Common with Moderate Decline (Common-20%; $N_0 = 350; \bar{\lambda} = 0.977$), Common with Rapid Decline (Common-50%; $N_0 = 350; \bar{\lambda} = 0.933$), Rare with Moderate Decline (Rare-20%; $N_0 = 100; \bar{\lambda} = 0.977$), and Rare with Rapid Decline (Rare-50%; $N_0 = 100; \bar{\lambda} = 0.933$; Table 1).

Typical occupancy monitoring for wildlife involves dividing a landscape into equal sampling units representative of a species' average home range size (MacKenzie et al., 2018; O'Connell and Bailey, 2011). To reflect this approach, we divided the study area into 56 km^2 square grid cells representing a female home range size (Table 1; Ellis et al., 2015; Krohner et al., 2022; Olson et al., 2014). We restricted sampling to grid cells where at least 50% of the cell met the minimum habitat threshold for placing simulated home range centers (habitat suitability ≥ 0.1), resulting in 455 grid cells in the study area (Table 1). For each year and population, we aggregated the raster representing the probability of use of at least one individual to the grid cell resolution (Fig. 1C; Ellis et al., 2015). We simulated each grid cell being sampled a maximum of six times within a year by creating an encounter history for each grid cell. We used a Bernoulli random draw for each sampling occasion with a probability equal to the probability of use of at least one individual for the respective grid cell and year (Ellis et al., 2015). These encounter histories represented whether an individual would have been detected in each grid cell for each sampling occasion under perfect detection probability ($p = 1$) with 1 representing detection and 0 representing non-detection (Fig. 1D). We repeated the entire population simulation process 100 times for each of the six population parameters sets, resulting in 600 perfect detection encounter histories, each spanning the initial year and subsequent ten years.

To simulate wildlife occupancy monitoring more realistically, we resampled perfect detection encounter histories to represent realistic detection probabilities for fisher surveys. Within occupancy modeling, detection probability represents the likelihood of detection given at least one individual is present in the grid cell at a single sampling occasion. As such, these per-occasion detection probabilities were calculated as:

$$\boldsymbol{p} = \boldsymbol{p}_{sim} {}^{*} \boldsymbol{p}_{pres} \quad (1)$$

where p_{sim} represents the probability of detecting an individual, if present, within a given cell during a given sampling occasion (Ellis et al., 2014). We set p_{sim} to 0.8 to represent high detection probability, and 0.3 to represent low detection probability (Table 2; Fig. 2). The probability that an individual is present in a given cell during a given sampling occasion (p_{pres}) varied across population sets, years, and grid cells. Once resampled for each value of p_{sim}, we subset the encounter histories to simulate both spatial and effort variability in scenarios where each year consisted of three, four, five, or six sampling occasions (Table 2; Fig. 2). In total, we simulated 909,600 encounter histories which represented all population sets for each combination of sampling parameters (Fig. 2).

2.2. Spatial variability

To account for spatial variability, we subset the simulated encounter histories by randomly selecting different grid cells to be sampled each year while keeping the total number of grid cells constant. This approach represents an aggregation of variable surveys where the sampling location varies between years, typically due to project turnover. We simulated a range in proportion of landscape sampled by sub-setting encounter histories so that numbers of grid cells sampled were 5% to 55% of the total landscape in increments of 10%. Because some sampling occurs in the same locations for more than one year, we also held a portion of sampled cells constant in some simulations (i.e. a proportion of the sampled grid cells were randomly selected to be sampled throughout all years). This proportion was set to 5% to 95% of total grid cells in 10% increments, as well as 0% and 100%, and is hereafter referred to as the percentage of spatial consistency. For example, if simulations with a 55% sampling of the landscape had a 15% spatial consistency in sampling, 250 of the 455 total grid cells are sampled each year (55%) and of those, 212 were randomly selected each year and 38 (15%) were consistently sampled in all years. Because there are a limited number of grid cells, some proportion will likely get sampled in multiple years regardless of assigned levels of spatial consistency, and this increases as the total number of grid cells sampled increases. As an additional point of reference, current wildlife occupancy sampling is

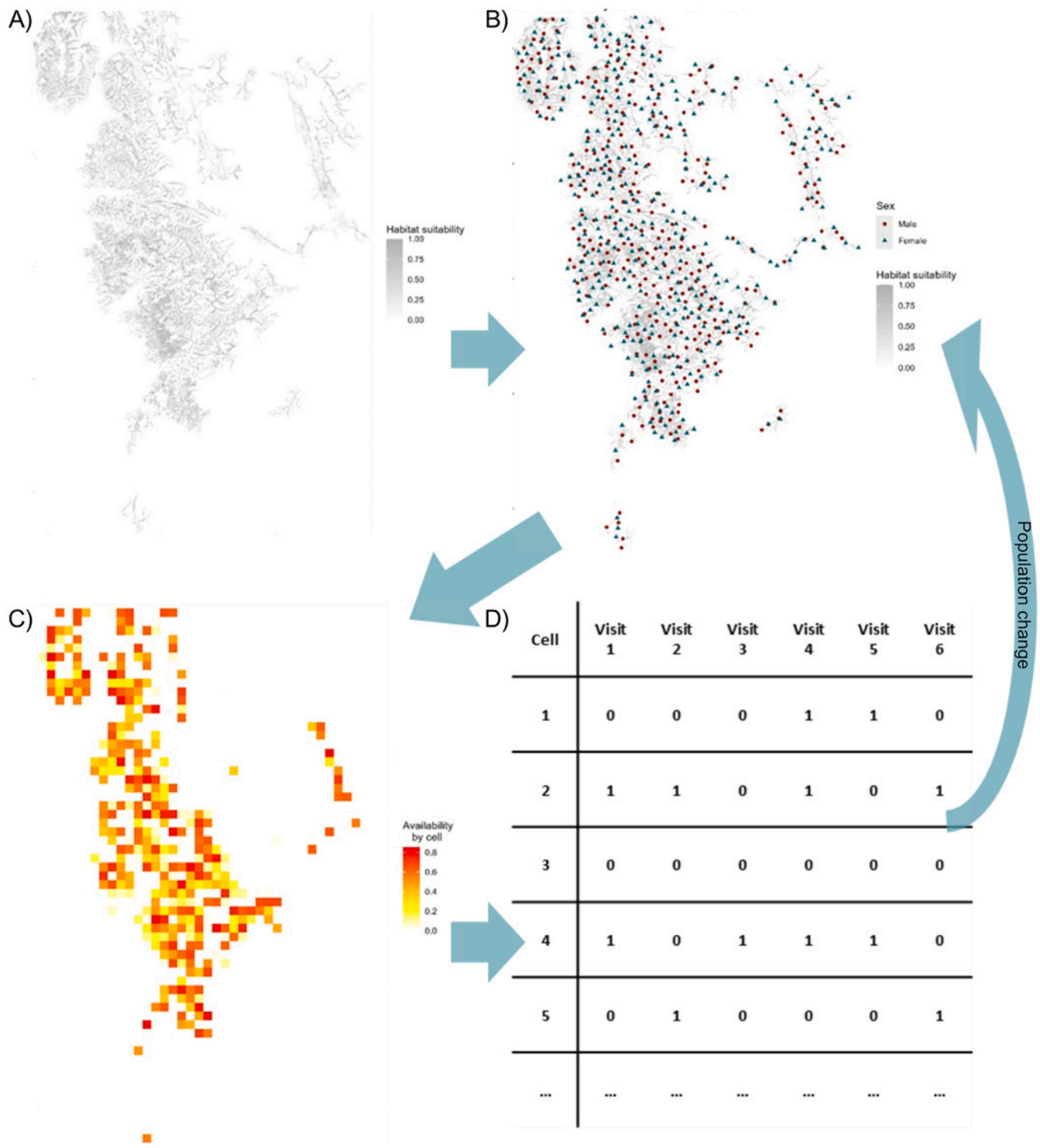

Fig. 1. Flow diagram showing the simulation process for a singular population scenario replicate. A habitat suitability raster (A) is used to place individuals of different sexes across the landscape (B) based on provided population parameters. In this example, the habitat suitability is representative of fisher distribution in northern Idaho and western Montana, USA, as described by Olson et al. (2014). Provided movement parameters are then used to create a raster layer representing the probability of use of at least one individual. This raster is aggregated up to the desired grid cell size (C) and used to create an encounter history for each grid cell for that year (D). For each subsequent year, a change in the population is simulated under an exponential growth model and removal or addition of individuals across the landscape. The probability of use rasters and encounter histories are then recalculated. These encounter histories are later subset and used in a robust design multi-season occupancy model to predict the trend in occupancy for that population scenario and replicate.

typically conducted with 100% spatial consistency, where all grid cells are consistently sampled every year (Larsen et al., 2001; MacKenzie et al., 2018; Mackenzie and Royle, 2005).

2.3. *Effort variability*

Effort variability reflects temporal variation in survey efforts, leading to variation in the amount of the landscape sampled each year. Often,

Table 2
Sampling design parameters with a brief description and the ranges of values simulated for each type of sampling design. Values in bold varied between different sampling design types. All sampling designs were tested on all population sets, as described in Table 1.

Parameter	Sampling Design		
	Consistent Sampling	Spatial Variability	Effort Variability
Proportion of total landscape that was available for sampling	**0.05, 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75, 0.85, 0.95**	**0.05, 0.15, 0.25, 0.35, 0.45, 0.55**	**1**
Total number of sampling occasions within a year		3, 4, 5, 6	
Per visit probability of detecting an individual given that at least one individual is present $p = p_{sim} * p_{presence}$		0.3, 0.8, 1	
Proportion of sampled cells that were forced to be spatially consistent, meaning those cells were sampled in all years	**1**	**0, 0.05, 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75, 0.85, 0.95, 1**	**0**
Median proportion of the total available cells that were actually sampled every year	**0.05, 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75, 0.85, 0.95***	**0.05, 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75, 0.85, 0.95***	**0.0374, 0.0637, 0.0879**
Minimum proportion of available cells that was required to be sampled each year	**0.05, 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75, 0.85, 0.95***	**0.05, 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75, 0.85, 0.95***	**0, 0.025, 0.05**

* For consistent sampling and spatial variability, the proportion of the landscape sampled did not vary between years. These values represent the actual proportion sampled every year.

due to financial and logistic limitations of sampling a large landscape, only a small proportion of landscapes is sampled in each year. However, on rare occasions, a larger proportion of the landscape may be sampled within a year when resources are available. To replicate this non-normal distribution of sampling proportions, we used a random draw from a beta distribution ($\alpha = 1.5, \beta = 30$) to determine which proportion of the 455 available grid cells was sampled each year. We used these sampling proportions to subset the respective annual encounter histories of each population.

With effort variability, we set spatial consistency to 0% because the number of grid cells sampled changed every year. In a year where very few grid cells are sampled, effort variability could result in some proportion of spatially consistent cells not being sampled. Not sampling spatially consistent cells in some years would contradict our definition of spatial consistency, where specific grid cells are sampled every year.

2.4. Baseline survey efforts

In addition to evaluating the statistical power of variable surveys, we investigated a baseline sampling scenario, where a consistent sampling effort would occur every year in addition to variable surveys. Baseline sampling was not spatially consistent, meaning sampling locations were allowed to vary each year, and instead represented a minimum proportion of the landscape to be sampled. For these simulations, the amount of the landscape sampled each year was the sum of the proportion of the landscape covered by baseline sampling, γ_{base}, and variable surveys, γ_{var}. We set γ_{base} to 2.5% and 5% of the total landscape (11 and 23 grid cells, respectively) to represent a realistically feasible amount of sampling that could be consistently conducted every year. We used a random draw from a beta distribution ($\alpha = 1.5, \beta = 30$) for γ_{var} for each year.

We compared effort variability with and without baseline survey efforts to consistent sampling. For these consistent sampling simulations 4, 6, and 9 percent of the landscape was sampled every year with 100% spatial consistency.

2.5. Analysis

2.5.1. Occupancy trend estimates and statistical power

After subsetting the encounter histories, we used the R package RMark to fit a robust-design multi-season occupancy model for each scenario and population in Program Mark (Ellis et al., 2015; Laake, 2013; White and Burnham, 1999). We used the resulting occupancy estimates to fit a linear trend model with a random effect of year in `RMark` using the variance components procedure with restricted maximum likelihood estimation (Ellis et al., 2015; Laake, 2013; White and Burnham, 1999). We then calculated the statistical power of each individual sampling design as the proportion of population replicates whose occupancy trend estimate and corresponding 90% confidence interval did not overlap zero and matched the directionality of the known trend in abundance for the simulated population (Ellis et al., 2015). Because we simulated all populations to experience a decline in abundance, the statistical power represented the proportion of population replicates whose estimated occupancy trend confidence intervals were entirely below zero.

In addition to calculating statistical power of each sampling design for each population set, we graphically compared the annual occupancy estimates and occupancy trend estimates for each population under the different sampling designs. These comparisons were used to evaluate the precision of these estimates under the different sampling designs.

2.5.2. True occupancy and relative decline

For each population, we calculated the true occupancy and relative decline of each population to evaluate the precision and accuracy of the occupancy and trend estimates for each sampling design. The true occupancy, ψ_t, for each population in each year, t, was calculated as:

$$\boldsymbol{\psi_t} = \frac{\sum_{n=1}^{N}(1-\theta_n^V)}{\boldsymbol{N}} \quad (2)$$

where θ_n represents the probability that no individuals are present in cell n, for the total number of grid cells, N, and over the course of V sampling occasions. Occupancy at this resolution represents a similar value of occupancy as would be calculated by monitoring programs at a resolution equal to that of the grid cell size. Using the calculated true occupancy for the initial (ψ_0) and final year (ψ_T), we also calculated the relative decline in occupancy for each population over all years as:

$$\Delta\boldsymbol{\psi} = \frac{\boldsymbol{\psi}_0 - \boldsymbol{\psi}_T}{\boldsymbol{\psi}_0} \quad (3)$$

We averaged these values for each set of population parameters and then graphically compared to the estimated annual occupancy and estimated occupancy trend for each population under each sampling design.

3. Results

3.1. Simulated populations

For population sets simulating density representative of an abundant species (Abundant-50% and Abundant-20%), average initial occupancy, $\overline{\psi}_0$, was 0.924 (SD = 0.008). Population sets with density representing a common species (Common-50% and Common-20%) had an average initial occupancy of 0.677 (SD = 0.015). Lastly, population sets with a density representative of a rare species (Rare-50% and Rare-20%) had an average initial occupancy of 0.257 (SD = 0.015). Rapid decline population sets – Abundant-50%, Common-50%, and Rare-50% – saw an average relative decline in occupancy of 29.97% (Abundant-50%; SD =

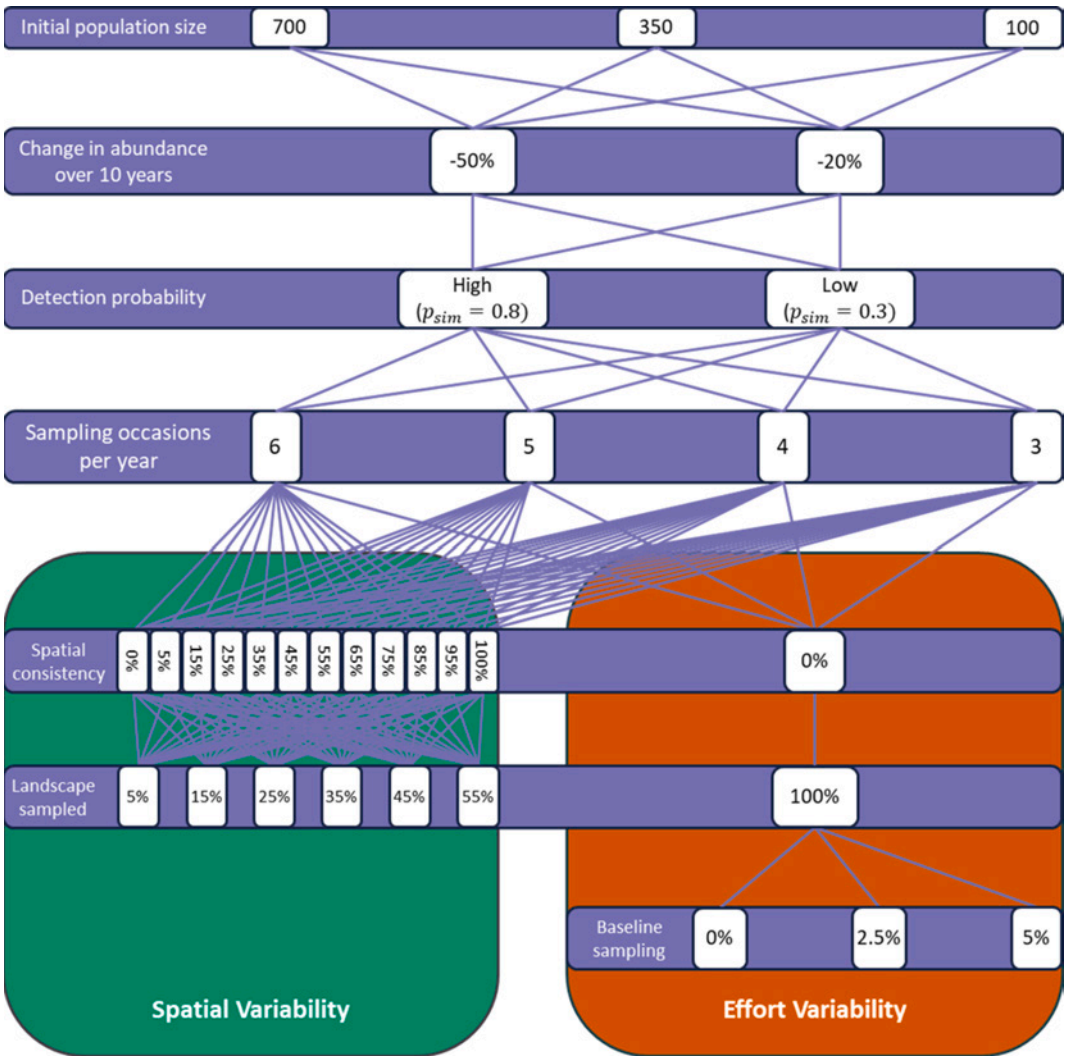

Fig. 2. Flowchart schematic of simulation parameters for variable sampling. Each purple row represents one parameter with its corresponding values in white. For each path from top to bottom of the chart 100 replicate populations were simulated and analyzed for statistical power, resulting in a total of 909,600 simulated scenarios and populations. Each colored column at the bottom of the chart represents the different sampling strategies that were simulated (spatial variability, and effort variability) and the corresponding parameters that were tested within that strategy. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

1.70%), 40.12% (Common-50%; SD = 1.93%), and 47.73% (Rare-50%; SD = 3.92%). Alternatively, the moderate decline population sets – Abundant-20%, Common-20%, and Rare-20% – experienced an average relative decline in occupancy of 9.12% (Abundant-20%; SD = 1.05%), 14.59% (Common-20%; SD = 1.43%) and 19.09% (Rare-20%; SD = 2.46%). Under Equation (1), when $p_{sim} = 0.8$, the average per sampling occasion detection probability, $\bar{p}$, ranged from 0.350 to 0.510 for each population set (see Table 3 for a breakdown by population set). For $p_{sim} = 0.3$, under Equation (1), the average per sampling occasion detection probability, $\bar{p}$, was between 0.135 and 0.200 (see Table 3 for a breakdown by population set).

3.2. Spatial variability

Under simulations of spatial variability, statistical power was consistent for each population's combination of p_{sim} value and percent of

Table 3
Summary of parameter values in simulated population sets.

Parameter	Population Sets					
	Abundant, Rapid Decline	Abundant, Moderate Decline	Common, Rapid Decline	Common, Moderate Decline	Rare, Rapid Decline	Rare, Moderate Decline
Average Initial Occupancy (SD)	0.924 (0.008)		0.677 (0.015)		0.257 (0.015)	
Average Relative Occupancy Decline (SD)	29.97% (1.70%)	9.12% (1.05%)	40.12% (1.93%)	14.59% (1.43%)	47.73% (3.92%)	19.09% (2.46%)
Average per Sampling Occasion Detection Probability (SD); psim = 0.8	0.510 (0.034)	0.510 (0.033)	0.420 (0.043)	0.418 (0.042)	0.357 (0.075)	0.350 (0.075)
Average per Sampling Occasion Detection Probability (SD); psim = 0.3	0.200 (0.033)	0.200 (0.034)	0.165 (0.044)	0.165 (0.044)	0.136 (0.070)	0.135 (0.071)

the landscape sampled, regardless of spatial consistency (Fig. 3, Appendix A; average range of statistical power for all spatial consistency values = 0.095 [p_{sim} = 0.8; SD = 0.064), and 0.137 (p_{sim} = 0.3; SD = 0.046]). In addition, variability in annual occupancy estimates was up to 1.7 times larger when the fewest grid cells were sampled compared to when the most grid cells were sampled, regardless of spatial consistency (Fig. 4, Appendix B; 23 grid cells, SD = 0.161–0.166, 250 grid cells, SD = 0.090–0.091).

3.3. Effort variability

In simulations of effort variability, a median of 3.74% (17 grid cells; SD = 0.13%, 0.59 grid cells) of the landscape was sampled each year. When comparing these simulations with a similar proportion of the

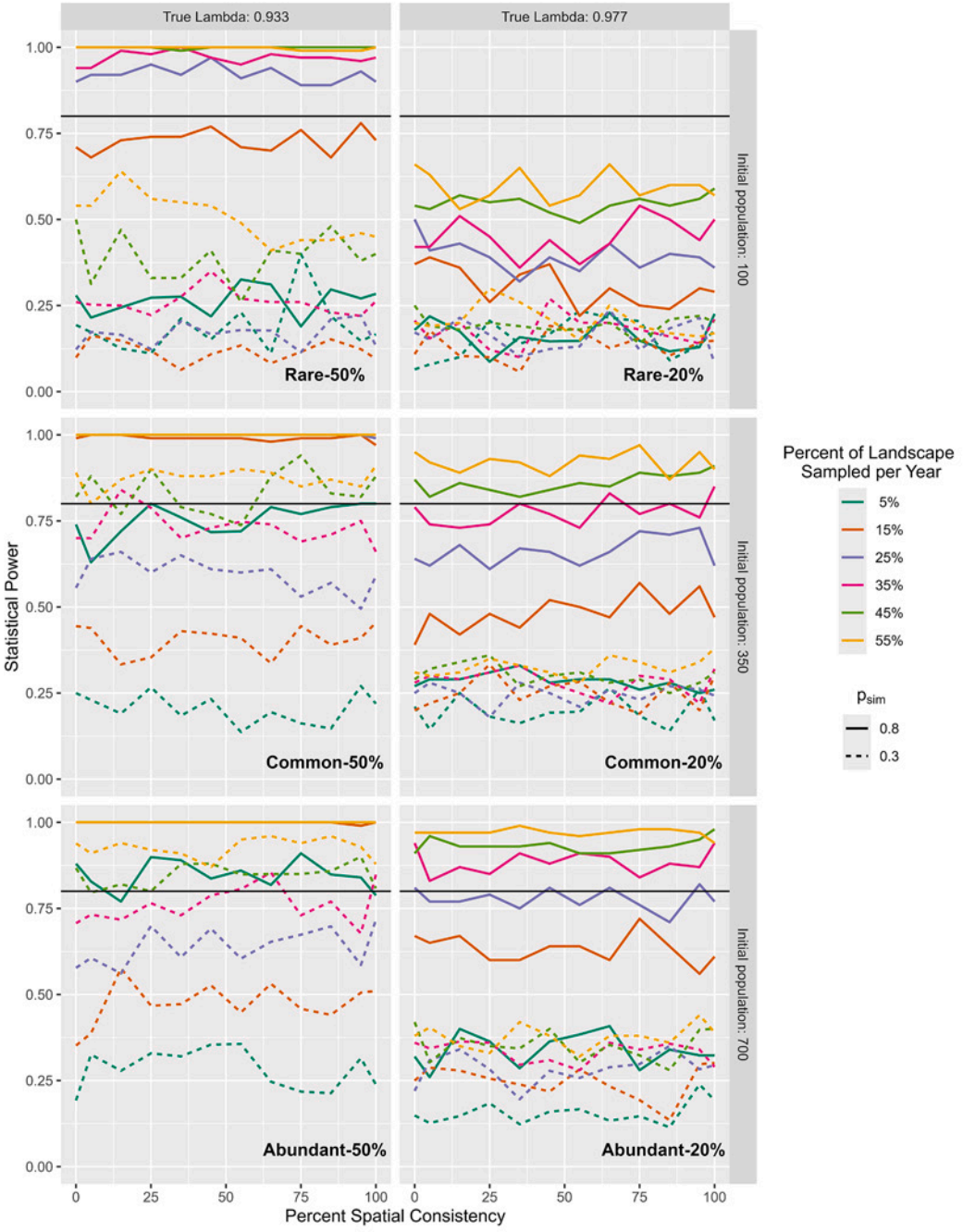

Fig. 3. Effects of spatial variability on the statistical power of sampling designs. Spatial consistency is represented along the x-axis by the percent of sampled cells that are sampled in all years. 25% spatial consistency means that of the grid cells sampled, 25% of those cells are the same every year while the other 75% are randomly chosen for each year. Traditionally, monitoring programs often operate at a spatial consistency of nearly 100%, where the same grid cells are sampled every year. Statistical power (y-axis) is calculated as the proportion of population replicates where the occupancy trend estimate indicated a decline and the 90% confidence interval did not overlap 0. A target statistical power of 0.80 is indicated by the black horizontal lines. Different simulated per sampling occasion detection probabilities are represented by solid (high detection probability; p_{sim} = 0.8) and dashed (low detection probability; p_{sim} = 0.3) lines. Line colors indicate the total proportion of the landscape that was sampled. All graphs represent sampling designs with 4 sampling occasions per year. Each panel relates to a single population scenario as indicated by the text in the bottom right-hand corners.

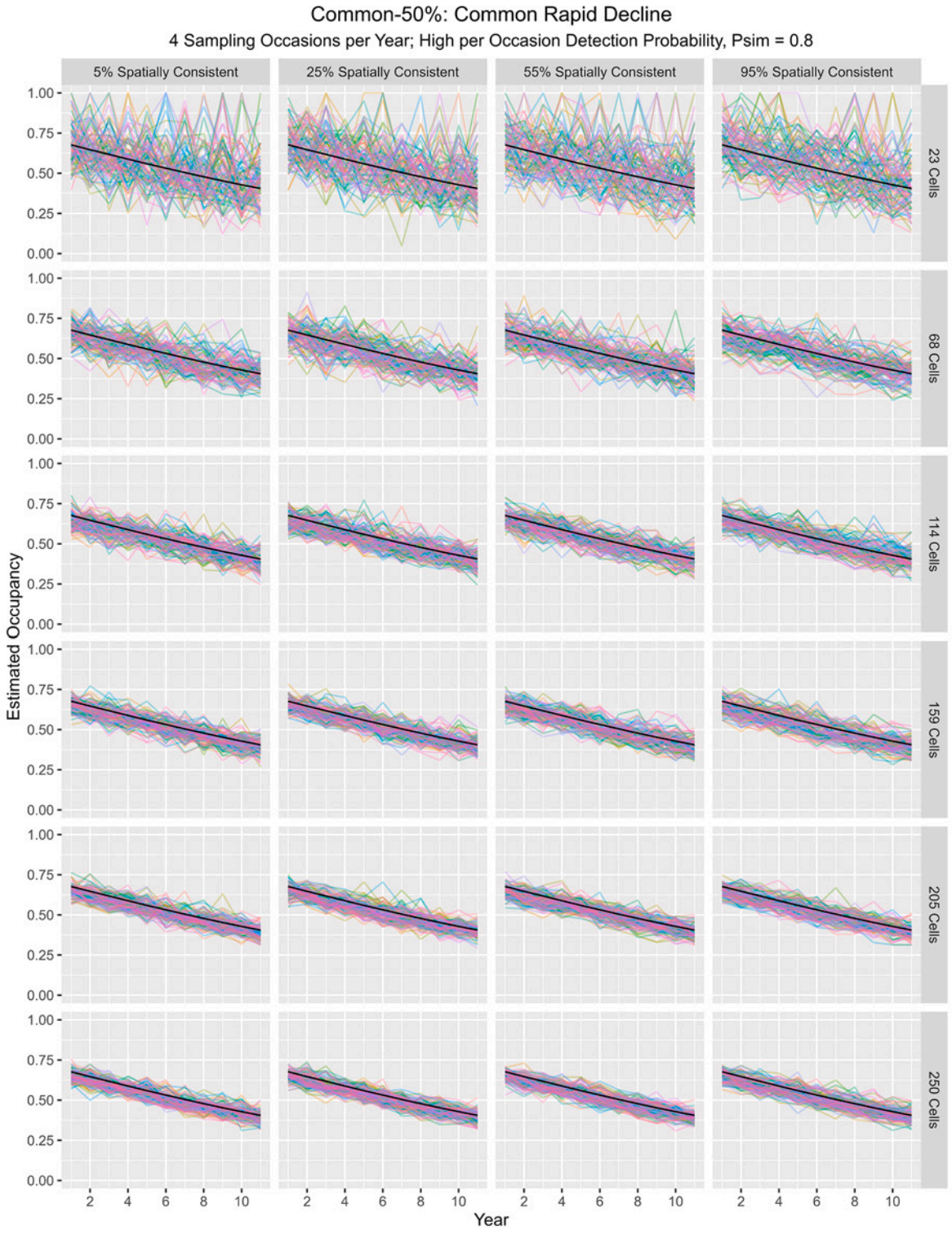

Fig. 4. Annual occupancy estimates for spatial variability simulations under high detection probability ($p_{sim} = 0.8$) and four total sampling occasions within a single year for the common with rapid decline population set (Common-50%; initial population size = 350 individuals, true $\lambda = 0.933$). Occupancy estimates are calculated with `RMark` and Program Mark in a robust design occupancy model based on simulated encounter histories. Years are numbered one through eleven with one being the initial population before a decline is simulated. The first removal of individuals occurs between year one and year two. Thick black line indicates the true annual occupancy value as calculated with Eq. (2). Individual colored lines represent the occupancy estimates for each year for one replicate of the population. Graphs going from left to right are sampling designs with increasing spatial consistency as measured by the percent of the sampled cells that are held consistent each year. Graphs moving from top to bottom represent an increasing total amount of grid cells sampled.

landscape consistently sampled annually (4%), statistical power was lower when effort varied annually for all high detection probability scenarios and population sets with common and abundant densities and a 50% abundance decline (Common-50%, Abundant-50%)(average difference in statistical power of 0.1738 [Common-50%; SD = 0.1171] and 0.1174 [Abundant-50%; SD = 0.0446]; green lines, middle and bottom left, Fig. 5, Appendix C). This difference was less prominent in populations with common or abundant density and only a 20% abundance decline (Common-20%, Abundant-20%) which showed an average difference in statistical power of 0.0963 (Common-20%; SD = 0.0293) and 0.0220 (Abundant-20%; SD = 0.0800) (green lines, middle and bottom right, Fig. 5, Appendix C). In contrast, both population sets

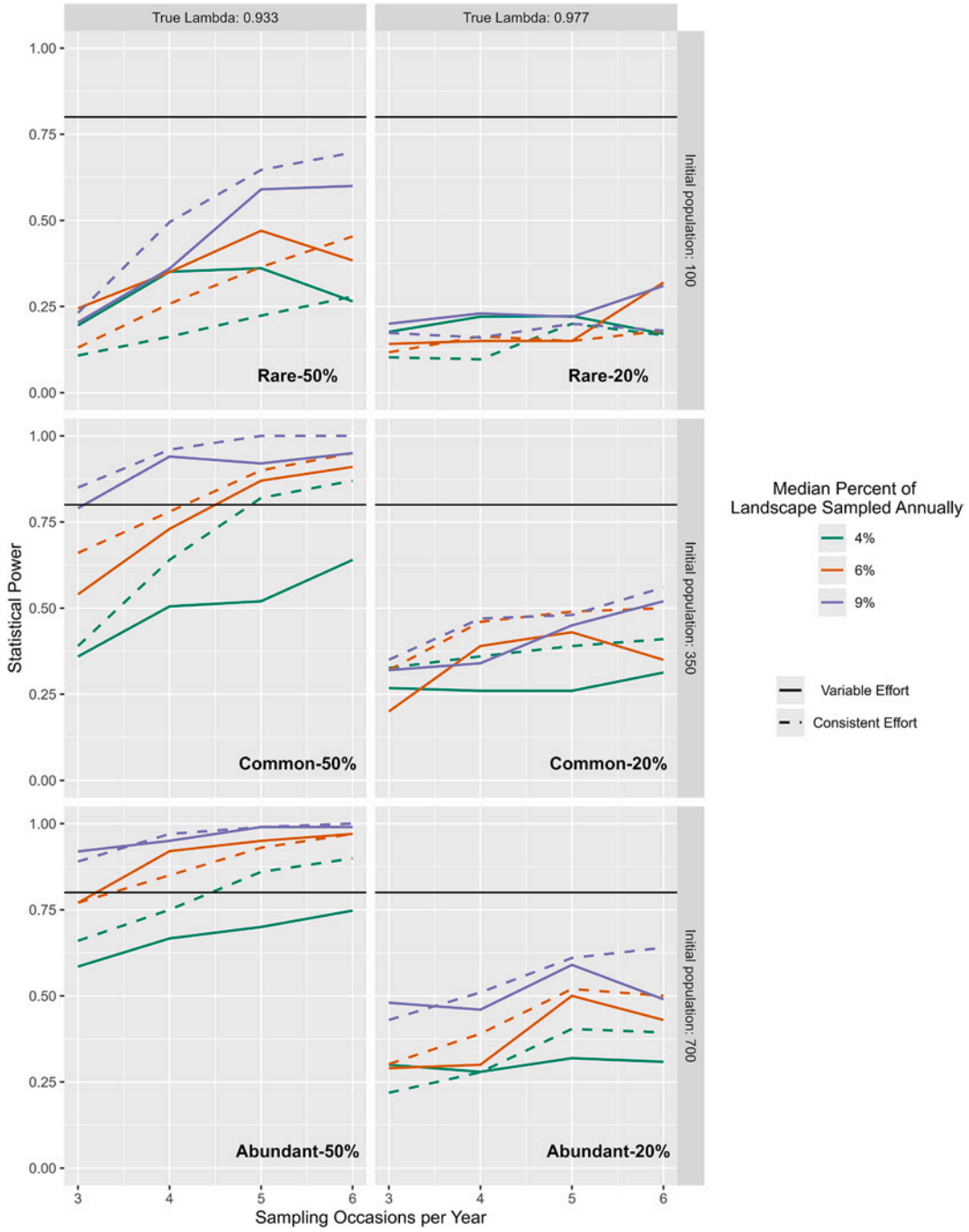

Fig. 5. Effects of effort variability on statistical power of occupancy monitoring under high per sampling occasion detection probability ($p_{sim} = 0.8$). Statistical power (y-axis) is calculated as the proportion of population replicates where the occupancy trend estimate indicated a decline and the 90% confidence interval did not overlap 0. Sampling occasions per year are indicated along the x-axis. As seen in previous studies, statistical power generally increases with increased number of sampling occasions and proportion of the landscape being sampled (indicated by different colored lines). Target statistical power of 0.80 is indicated by black horizontal line. Solid and dashed lines represent variable and consistent effort sampling strategies. Various colors represent the median amount of the landscape sampled. For consistent effort (dashed lines) the same amount of the landscape is sampled every year, while for variable effort this value changes annually with 4%, 6% and 9% being the median (green, orange and purple solid lines, respectively). Green solid line represents variable effort with no baseline sampling. Orange and purple solid lines represent variable effort with 2.5% and 5% baseline sampling, respectively, in addition to variable surveys. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

with the lowest population density showed higher statistical power (average difference in statistical power of 0.0998 [Rare-50%; SD = 0.0864] and 0.0560 [Rare-20%; SD = 0.0540]; green lines, top and middle, Fig. 5, Appendix C) when sampling effort was variable compared to consistent.

These results were consistent with the estimated occupancy trends for each population and effort variability scenario. Generally, all trend estimates reflected simulated abundance declines (green lines and box plots, Fig. 6, Appendix D) but confidence intervals around these estimates were smaller for larger populations. For these populations, the width of the occupancy trend confidence intervals was similar under both variable and consistent effort frameworks (solid vs. dashed lines and boxes in Fig. 6, Appendix D).

3.4. Baseline monitoring simulations

Under scenarios with 2.5% and 5% baseline sampling in combination with variable surveys, a median of 6.37% (29 grid cells; SD = 0.13%) and 8.79% (40 grid cells; SD = 0.13%) of the landscape was sampled each year, respectively. Under most population simulations, adding baseline monitoring to variable surveys resulted in statistical power that was more closely aligned with consistent sampling (average difference in statistical power: 0.0283, SD: 0.052; orange (2.5% baseline) and purple (5% baseline) lines, Fig. 5; Appendix C). Similar to effort variability simulations with no baseline sampling, occupancy trend estimates varied widely between replicates with large 90% confidence intervals (orange and purple solid lines and box plots in Fig. 6, Appendix D). For abundant and common population sets with a 50% decline in abundance (Abundant-50% and Common-50%), implementing baseline sampling resulted in greater precision of occupancy trend estimates when using variable effort (Fig. 6, Appendix D). This greater precision resulted in statistical power above the standard optimal of 0.80 in a majority of sampling scenarios for these populations (orange [2.5% baseline] and purple [5% baseline] lines, middle and bottom left, Fig. 5). The precision of occupancy trend estimates from variable surveys with baseline sampling was also similar to that of consistent sampling a similar percentage of the landscape (solid versus dashed boxes and lines in Fig. 6, Appendix D).

4. Discussion

Statistical power of a sampling design does not appear to rely on spatial consistency under any population scenario (Fig. 3; Appendix A). As the number of grid cells forced to be spatially consistent decreased, there was no significant decline in statistical power, counter to our expectations and traditional occupancy monitoring guidance. Generally, sampling design recommendations have cautioned against a lack of spatial consistency in sampling, suggesting that designs in which the location of sampling varies among years can only detect large population changes (Mackenzie and Royle, 2005; Steen et al., 2023). Differences in our results and previous simulations are likely driven by differences in monitoring designs and simulation processes. Previous simulations focused on a rotating panel design to represent spatial variation in sampling (Urquhart et al., 1998). These previous designs either included multiple panels of sampling locations that were cyclically surveyed or sampled only in a single year of the simulation (Urquhart et al., 1998), but sampling locations were never included in multiple panels. In contrast, our monitoring design included random selection of grid cells annually, with all cells being available for sampling regardless of how often they were previously sampled. Regarding the simulation process, our results likely differ from those of Steen et al. (2023) due to differences in methodology for simulating population decline. While Steen et al. (2023) allowed for spatial heterogeneity in their population, a proportional decline in the population was uniformly applied across the landscape, resulting in a spatially homogenous population decline that is uncharacteristic of true populations at a broad scale. In contrast, we distributed individuals on the landscape then imposed a population decline across the entire population with random individuals removed. Our approach resulted in spatial heterogeneity of the population and of the population decline. In analyses focused on true random annual site selection, Urquhart and Kincaid (1999) and MacKenzie et al. (2018) caution against an unbalanced design, suggesting that with spatial variation in sampling locations, statistical power is strongly and negatively correlated with variance among sites and could be confounded with temporal variation. In our simulations, various starting population sizes (N_0 = 700, 350, 100) correlate with differing variances in population density among sampling sites. Yet, under all initial population sizes, simulated occupancy monitoring scenarios were equally capable of detecting temporal trends in abundance, regardless of spatial consistency in sampling. These results likely reflect the independence and uniform precision of each year's occupancy estimate when a specific amount of the landscape is sampled, independent of the amount of spatial consistency.

Rather than spatial consistency, consistent effort appears to influence statistical power of long-term monitoring designs (Fig. 3 and Fig. 5). The number of sites sampled, or sampling effort, is often noted as one of the largest influences on statistical power when assessing study design and population characteristics, especially in sampling with high detection probability (Mackenzie and Royle, 2005; Steen et al., 2023; Urquhart and Kincaid, 1999). Impact of sampling effort was reflected in our simulation results where, in some cases, we saw dramatic declines in statistical power when allowing the number of sites sampled annually to vary (Fig. 5, Appendix C). These declines were likely caused by positive associations between numbers of grid cells sampled and precision of occupancy estimates. Occupancy estimates have much greater variability and larger confidence intervals, leading to lower statistical power, when less of the landscape is sampled (Fig. 4 and Fig. 6, Appendices B and D). Our simulations generally involved sampling a small percentage of a large landscape, and in our smallest population simulation there is a high level of variance between grid cells. Although this amount of sampling is reflective of the sampling that is likely to occur every year, the strong, negative correlation of statistical power with variance among sites led to an inability to consistently detect population trends when effort varied, and population sizes were low, or abundance declines were moderate (Larsen et al., 2001; MacKenzie et al., 2018; Urquhart and Kincaid, 1999). Implementing a consistent baseline sampling effort annually countered low statistical power, sometimes dramatically, despite spatial variability of baseline sampling (Fig. 5; Appendix C). Baseline sampling provides more sampling locations, thus increasing the precision of annual occupancy estimates, and increasing statistical power.

Standard convention for occupancy monitoring has been to sample the same grid cells, or in some cases even the exact same location, consistently over many years (Kendall et al., 2016; Larsen et al., 2001; MacKenzie et al., 2018; Mackenzie and Royle, 2005; Zielinski et al., 2013). This type of long-term consistent sampling is difficult for most groups interested in broad-scale population monitoring (Cash and Moser, 2000; Fraser et al., 2013; Steenweg et al., 2017). As an alternative, our findings build upon current suggestions of collaborative monitoring frameworks by supporting the possibility of incorporating existing local and small-scale survey efforts undertaken with a standardized protocol (Beaudrot et al., 2016; ENETWILD-consortium et al., 2023; Reichert et al., 2021; Rovero and Ahumada, 2017). Although a standard protocol would necessarily focus on how surveys are conducted in order to achieve high detection probabilities, it could allow flexibility in the amount and location of survey efforts. Spatial flexibility would allow aggregation of many standardized surveys, such as those conducted as part of the legal process prior to major environmental actions. Collaborative programs would likely require a minimum amount of the landscape to be surveyed every year as a baseline effort. This baseline effort could be minimal and still allow for detection of broad-scale population trends. Project specific power analyses should be

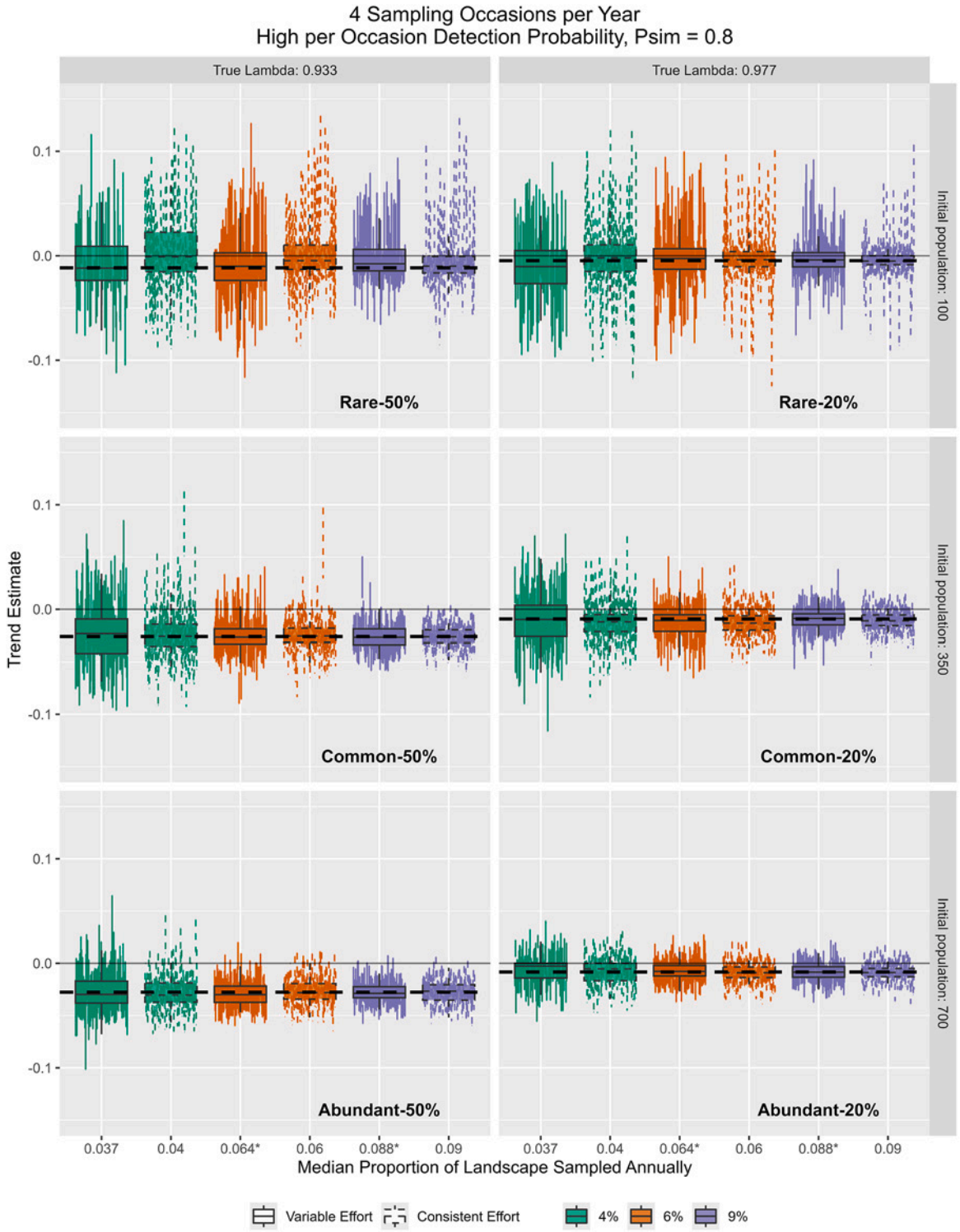

Fig. 6. Occupancy trend estimates for each population replicate with 90% confidence interval (vertical bars) under annually variable (solid lines and boxes) and consistent (dashed lines and boxes) effort. Various colors represent the median amount of the landscape sampled. For consistent effort (dashed lines) the same amount of the landscape is sampled every year, while for variable effort this value changes annually with 4%, 6% and 9% being the median (green, orange and purple solid lines, respectively). Green solid line represents variable effort with no baseline sampling. Orange and purple solid lines represent variable effort with 2.5% and 5% baseline sampling, respectively, in addition to variable effort surveys. All scenarios shown here are with high per sampling occasion detection probability (p_{sim} = 0.8) and four sampling occasions per year. Thick black dashed horizontal line indicates the true occupancy trend for the population as calculated in Eq. (3). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

conducted to determine the appropriate amount of baseline sampling; however, in some of our scenarios a baseline survey effort of 5% of the landscape could allow for reliable detection of declines in a population when combined with existing variable surveys.

It may also be possible for long-term or large-scale monitoring programs to be more flexible in their sampling efforts. Often, within a year, projects face unpredictable challenges to sampling their established locations. These challenges can range from wildfires and unexpected weather problems to global pandemics and can severely limit the locations that are available for sampling. In these scenarios, because spatial consistency does not appear to affect statistical power of the monitoring program, simply sampling different locations could still allow for accurate detections of trends in the regional population of interest.

Although our best attempts were made to simulate a realistic population and sampling, we do recognize some parameters may differ in real world scenarios. In our simulations, individuals were placed randomly in locations that met a baseline habitat threshold. In reality, populations may be more patchily distributed across a heterogeneous landscape. Patchy distribution would result in a higher variance between grid cells and likely require a greater amount of sampling to detect population trends. Additionally, our sampling locations were selected randomly, when in reality sampling may be clustered, particularly when areas are difficult to access, or resources are limited. Future analysisinto the effects of variable sampling on statistical power when sampling locations are not randomly distributed would be helpful.

Our sampling simulation also assumed that all grid cells were sampled in entirety with a uniform number of sampling occasions per year and a constant value of p_{sim} across years and grid cells. Grid cells were only sampled if they contained $\geq$50% quality habitat. Realistically, these parameters and how grid cells are selected for sampling can vary greatly among projects. Because how grid cells are sampled can drive statistical power, further investigation is needed to understand the effects of variable sampling protocols on collaborative population monitoring efforts (Ellis et al., 2014; Guillera-Arroita and Lahoz-Monfort, 2012; Steenweg et al., 2016; Tucker et al., 2021).

Our results support monitoring strategies that provide consistent sampling effort, which was more important than annual spatial consistency. Such an approach provides greater sampling flexibility and the ability to incorporate sampling from different entities and organizations. We believe this flexibility allows for collaborative programs to better leverage existing local efforts, provided the use of a common protocol. This strategy can greatly reduce financial and logistical burdens of broad-scale wildlife population monitoring for rare species.

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CRediT authorship contribution statement

Jordan L. Heiman: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jody M. Tucker:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Sarah N. Sells:** Writing – review & editing, Supervision, Conceptualization. **Joshua J. Millspaugh:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization. **Michael K. Schwartz:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

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.

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Data availability

GitHub repository of all code used for simulations: https://github.com/Jordan-Heiman/rSPACE_Modification

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