QUANTIFYING, MONITORING, AND MANAGING BIODIVERSITY ACROSS MULTIPLE SPATIAL SCALES

By

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ABSTRACT

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This dissertation aims to investigate how science can effectively inform management and policy decisions, leading to positive conservation outcomes for vulnerable wildlife communities. Successful conservation requires the incorporation of ecological uncertainty and socio-ecological complexity into the decision-making process. To navigate the uncertainty and complexity pertinent to landscape conservation, I demonstrate a multi-scaled approach to quantify, monitor, and manage amphibians in a case study of a regional network of national parks. In Chapter 1, I quantify biodiversity across multiple spatial scales by fitting a multi-region community occupancy model to regional amphibian monitoring data to elucidate the drivers and threats(s) to biodiversity and the relevant scale(s) to target management. In Chapter 2, I explore the efficacy of different monitoring programs and identify strategies to monitor biodiversity across multiple spatial scales to minimize uncertainty in system dynamics. In Chapter 3, I predict the impacts of, and then spatially prioritize, management to increase biodiversity across multiple spatial scales by incorporating governance complexity in the decision-making process. In Chapter 4, I synthesize findings from previously published studies to determine the extent, and conditions under which, decision support frameworks can lead to positive conservation outcomes. The chapters of this dissertation provide critical guidance on how to scale up conservation science to match the scope and scale of the ecological systems and governance structures it is meant to inform. The application of this knowledge can help conservation scientists, managers, and policy makers address the complex and multi-scaled biodiversity crisis.

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INTRODUCTION

In the midst of the Anthropocene, we are experiencing an unprecedented era of environmental challenges. Ecosystem degradation and subsequent losses in biodiversity are occurring at alarming rates (Johnson et al. 2017). The rate of biodiversity loss is predicted to increase markedly over this century (Leclère et al. 2020), with extinction risk for bird and mammal species predicted to more than double by 2060 (Tilman et al. 2017). Despite clear global goals and commitment to maintaining biodiversity (e.g. the 2020 Aichi Targets; Convention on Biological Diversity 2010), progress in addressing biodiversity loss has not been sufficient to reach the stated targets (Tittensor et al. 2014, Diaz et al. 2019).

The challenges associated with preventing biodiversity loss are not just enormous, but immensely difficult to solve. The pressing issues of the day are 'wicked'—clouded in uncertainty, complexity, and conflicting or competing interests (Game et al. 2013). Climate change, habitat loss, and other global threats to biodiversity are vast and complex—they directly or indirectly impact every organism on the plant. The extent of their reach thus encompasses a diversity of stakeholder interests, a high amount of system and future uncertainty, and complex, overlapping governance systems. As a result, solving these challenges requires the integration of the scope and scale of these problems directly into conservation science and decision making to effectively tackle the inherent uncertainties and diverse stakeholder interests.

Recognizing that ecological processes and governance structures are scaled hierarchically (Heffernan et al. 2014, Armsworth et al. 2015), it is necessary to similarly structure science and conservation across spatial scales to successfully address biodiversity threats and reach conservation targets. To achieve this, advanced analytical approaches are required to incorporate multi-scaled processes directly into statistical models, monitoring programs, and landscape conservation decision making. In this dissertation, I develop a multi-scaled modeling approach and apply it to a regional research and conservation program that aims to quantify, monitor, and manage amphibian biodiversity across a network of protected areas. In the sections below, I provide background description of this case study and an overview of the individual chapters that comprise this dissertation.

Case Study Background

Through the creation of the Inventory & Monitoring Program (I&M), the U.S. National Park Service (NPS) has established a long-term monitoring and research program of various natural resources to inform management of protected areas through the long-term monitoring and research of various natural resources (National Parks Omnibus Management Act of 1998). The National Capital Region Network (NCRN) is one of 32 administrative networks within the I&M Program that monitors a number of ‘vital signs’ to support and guide park management (NPS 2005). The NCRN encompasses 11 National Parks within the urbanized region surrounding Washington, DC in the mid-Atlantic region of the United States, which vary in their recreational, cultural, and natural resource objectives.

Amphibians are one of the fastest declining taxa globally, threatened by a myriad of additive and interacting stressors (Stuart et al. 2004, Hof et al. 2011, Grant et al. 2016). Chief among those threats are land use and climate change, as amphibians are bi-phasic and rely on climate- and land use-sensitive habitat (e.g., ephemeral wetlands) to complete their life cycle (Pounds 2001, Cushman 2006). The mid-Atlantic region of the United States is home to many wetland-breeding amphibian species, which are particularly vulnerable to the effects of climate change as rapidly increasing urbanization in the region isolates protected areas (Stottelemeyer 1987, Lookingbill et al. 2014). Amphibians were selected as a vital sign within the NCRN in part because they are (1) presumed to be useful indicators of environmental change; and (2) management actions aimed at improving habitat quality for amphibians will likely have ancillary benefits to other components of the ecosystem (NPS 2005).

Across the I&M networks, there is a desire to detect, understand, and respond to declines in vital signs, but there are few examples of how this might be accomplished at a broad scale. Park resource managers and regional staff in the NCRN have demonstrated interest in linking monitoring data to management decisions for amphibian communities (Grant et al. 2013). The challenge is to identify strategies to improve amphibian biodiversity at the regional scale in the face of threats to park resources, while incorporating monitoring data and differing management objectives from individual parks. Incorporating a multi-scaled approach to this challenge provides a synthesis of amphibian community data with immediate relevance for monitoring and managing amphibian populations throughout the NCRN. Beyond this case study, this work illustrates an approach for understanding, predicting, and evaluating impacts of environmental changes and management responses in landscape conservation.

Dissertation Overview

In the first three chapters, I develop a multi-scaled framework demonstrating how to *quantify* (Ch. 1), *monitor* (Ch. 2), and *manage* (Ch. 3) biodiversity in a landscape conservation case study. More broadly, this research revolves around the following central question: *how do we ensure science directly informs management and policy decisions, leading to positive* *conservation outcomes?* Thus, I follow the first three chapters with a broader reflection on the application of decision support frameworks in conservation.

In Chapter One I describe how to *quantify* biodiversity patterns across spatial scales. I fit a multi-region community occupancy model to 13 years of monitoring data on amphibians in the NRCN, revealing the magnitude and direction of effects on amphibian biodiversity patterns from ecological drivers (habitat area, connectivity, and quality) at both local and regional scales. I also highlight how the spatial scale of observation and analysis can influence statistical inference on a study system and its dynamics. This approach can be applied to other systems in which conservation professionals must determine the drivers of relevant biodiversity patterns and the spatial scale(s) at which management should be addressed.

In Chapter Two I present how to *monitor* biodiversity patterns across spatial scales. I simulate data obtained via different large-scale monitoring designs and evaluate the bias and precision of occupancy parameter estimates describing the status, trends, and drivers of wildlife communities at both local and regional scales. These results can be used to modify the existing regional monitoring design by evaluating tradeoffs in each parameter and/or scale. Further, this chapter offers general guidance concerning the design of large-scale monitoring programs needed to inform conservation management.

In Chapter Three I present how to *manage* biodiversity across spatial scales. I use parameter estimates from the multi-region occupancy model (described in Ch. 1) to predict the impacts of wetland management on amphibian diversity and demonstrate how to spatially prioritize management actions relative to objective weights that vary by stakeholders within and among spatial scales. These results provide a framework for the NCRN to spatially prioritize management (using limited resources) to conserve the amphibians. Beyond the application of the case study, I provide a framework that can incorporate the complexity of large, multi-scaled ecological systems and governance structures into the conservation decision making process.

In Chapter Four I present how decision support frameworks can be used to achieve desired conservation outcomes. In this chapter, I review previously published amphibian conservation studies that use a decision support framework to evaluate how the use of these frameworks does, or does not, help reach defined conservation objectives and to identify barriers for implementing recommended decisions. These findings provide a plan of action to help guide the application and development of decision support frameworks to ensure science effectively informs decisions and leads to positive conservation outcomes.

Despite the specificity of the case study, the frameworks I developed here are broadly applicable to other species and systems given that the overall goal of my dissertation research is to infuse multi-scale considerations into hierarchical models and decision making. With these approaches, researchers and managers can conduct analyses and implement management efforts at scales that are relevant for conservation planning. By doing so, we are one step closer to addressing global biodiversity loss more effectively.

CHAPTER 1: A HIERARCHICAL ANALYSIS OF HABITAT AREA, CONNECTIVITY, AND QUALITY ON AMPHIBIAN DIVERSITY ACROSS SPATIAL SCALES

Abstract

Habitat fragmentation can alter species distributions and lead to reduced diversity at multiple scales. Yet, the literature describing fragmentation effects on biodiversity patterns is contradictory, possibly because most studies fail to integrate spatial scale into experimental designs and statistical analyses. Thus, it is difficult to extrapolate the effects of fragmentation to large-scaled systems in which conservation management is of immediate importance. To examine the influence of fragmentation on biodiversity across scales, we (1) estimated the effects of habitat area, connectivity, and quality at both local (i.e. community) and regional (i.e. metacommunity) scales; and (2) evaluated the direction, magnitude, and precision of these estimates at both spatial scales. We developed a multi-region community occupancy model to analyze 13 years (2005-2017) of amphibian monitoring data within the National Capital Region, a network of U.S. National Parks. Overall, we found a positive effect of park size and a negative effect of isolation on species richness at the park-level (i.e. metacommunity), and generally positive effects of wetland area, connectivity, and quality on species richness at the wetland-level (i.e. community), although parameter estimates varied among species. Covariate effects were less precise, but effect sizes were larger, at the local wetland-level as compared to the park-level scale. Our analysis reveals how scale can mediate interpretation of results from scientific studies, which might help explain conflicting narratives concerning the impacts of fragmentation in the literature. Our hierarchical framework can help managers and policymakers elucidate the relevant spatial scale(s) to target conservation efforts.

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CHAPTER 2: A COMPARISON OF MONITORING DESIGNS TO ASSESS WILDLIFE COMMUNITY PARAMETERS ACROSS SPATIAL SCALES

Abstract

Dedicated long-term monitoring at appropriate spatial and temporal scales is necessary to understand biodiversity losses and develop effective conservation plans. Wildlife monitoring is often achieved by obtaining data at a combination of spatial scales, ranging from local to broad, to understand the status, trends, and drivers of individual species or whole communities and their dynamics. However, limited resources for monitoring necessitates tradeoffs in the scope and scale of data collection. Careful consideration of the spatial and temporal allocation of finite sampling effort is crucial for monitoring programs that span multiple spatial scales. Here we evaluate the ability of five monitoring designs - stratified random, weighted effort, indicator unit, rotating panel, and split panel - to recover parameter values that describe the status (occupancy), trends (change in occupancy), and drivers (a site-specific covariate and an autologistic term) of wildlife communities at two spatial scales. Using an amphibian monitoring program that spans a network of U.S. National Parks as a motivating example, we conducted a simulation study for a regional community occupancy sampling program to compare the monitoring designs across varying levels of sampling effort (ranging from 10 to 50%). We found that the stratified random design outperformed the other designs for most parameters of interest at both scales, and was thus generally preferable in balancing the estimation of status, trends, and drivers across scales. However, we found that other designs had improved performance in specific situations. For example, the rotating panel design performed best at estimating spatial drivers at a regional level. Thus, our results highlight the nuanced scenarios in which various design strategies may be

preferred, and offer guidance as to how managers can balance common tradeoffs in large-scale and long-term monitoring programs in terms of the specific knowledge gained. Monitoring designs that reduce biases in parameter estimates are needed to guide conservation policy and management decisions in the face of broad scaled environmental challenges, but the optimal design is sensitive to the specific objectives of a monitoring program.

Introduction

Monitoring programs are essential for natural resource management as they provide data to address scientific questions, develop predictive models, trigger and guide management actions, and assess the impacts of policies and interventions in support of evidence-based conservation (Yoccoz et al. 2001, Sutherland et al. 2004, Nichols et al. 2006). The need for ecological monitoring has increased over the last several decades as global pressures have grown in severity and biodiversity loss has accelerated (Butchart et al. 2010, Nicol et al. 2019). However, determining the efficient allocation of limited resources is a critical impediment to the development of effective monitoring programs (Lindenmayer and Likens 2010, Buxton et al. 2020). This is particularly important when considering heterogeneous landscapes over large spatial scales and complex governance networks with multiple management jurisdictions (Carlson and Schmiegelow 2002, Bennett et al. 2018).

Recognition that biodiversity change stems from interacting local, regional, and global drivers (Keller et al. 2008, Lindenmayer and Likens 2010) has spurred the design of monitoring programs to match these scales (e.g., NSF NEON, Thorpe et al. 2016; TEAM, Beaudrot et al. 2016; USGS BBS, Sauer et al. 2017). Large-scale monitoring programs are used to track the status, trends, and drivers of wildlife species and communities across individual and/or independent spatial units. Such programs are often organized as part of a regional or national administrative network to detect and understand changes in biodiversity (Yoccoz et al. 2001). In contrast, conservation management decisions are often implemented at the local level (e.g., individual parks, refuges, etc.). As such, large-scale monitoring programs must be able to both detect biodiversity changes across broad scales while also providing specific information at local scales to inform management activities that can help mitigate declines when and where they arise (Adams and Muths 2019).

Designing and implementing robust monitoring programs to meet these multiple priorities, often with limited resources, remains a challenge (Scholes et al. 2008, Lindenmayer & Likens 2010, Jones 2011, Blanchet et al. 2020). Monitoring programs typically fall into one of three categories: ‘landscape’, ‘surveillance’, or ‘targeted’ (Eyre et al. 2011). These approaches range in spatial extent, information content, and purpose (Sparrow et al. 2020). Landscape monitoring primarily aims to measure population *status* (e.g., species distribution or abundance) through descriptive and spatially continuous information collected across broad spatial scales. Surveillance monitoring (sometimes referred to as omnibus monitoring) aims to detect and observe population *trends* through repeated, standardized surveys that can be conducted at local to broad spatial scales. Targeted monitoring aims to evaluate and understand the *drivers* of population dynamics through a hypothesis-driven approach that is often executed at small and discrete scales (Eyre et al. 2011). Yet, monitoring programs that accurately and precisely estimate status, trends, and drivers simultaneously across multiple scales are increasingly necessary for understanding, and reacting to, rapidly changing environmental conditions (Scholes et al. 2008, Albert et al. 2010, Sparrow et al. 2020).

Here, we evaluate the ability of different monitoring designs to make inference on wildlife species and community status, trends, and drivers within and across multiple management units and spatial scales. To do this, we conducted a simulation study comparing the effectiveness of common designs that combine various elements of targeted, surveillance, and landscape monitoring. We used a regional amphibian monitoring program within a network of mid-Atlantic National Parks as a case study (National Park Service 2005, Grant and Brand 2012). Like many natural resource agencies charged with large-scale monitoring initiatives, the National Capital Region Inventory & Monitoring Network of the U.S. National Park Service (NCRN, National Park Service 2005) wishes to maximize the information gained from annual amphibian occupancy surveys within budget constraints. The use of a relevant case study for our analyses ensures the logistical feasibility of each strategy and the real-world applicability of our simulation results. However, our approach is general in scope and thus our results should be broadly informative to researchers and managers developing sampling schemes across taxa, scales, and landscape configurations.

We reviewed existing large-scale monitoring programs to choose sampling designs that could allow the simultaneous estimation of species status (e.g., occupancy), trends, and drivers of species and community changes, and considered these in a hierarchical framework to allow inference across multiple spatial scales. Our comparisons focused on five commonly-employed monitoring designs: stratified random, indicator, rotating panel, split-panel, and weighted effort (each described in more details in the Methods). We simulated and assessed the effectiveness of the monitoring designs (i.e., the allocation of sampling sites across a network of independent units) across various levels of sampling effort (i.e., 10%, 20%, 30%, 40%, or 50% of available sites sampled across the total potential habitat). We evaluated the accuracy and precision of multi-region community occupancy parameter estimates, including metrics of population status (mean occupancy), trend (a year-specific effect), and drivers (a site-specific effect as well as a temporal autologistic effect), across two nested spatial scales. Our results quantify the tradeoffs of common designs for large- and multi-scale monitoring programs within the real-world context of allocation decisions regularly faced by management agencies.

Simulation Study

Large-scale Monitoring Designs

Five monitoring designs – stratified random, indicator, rotating panel, split-panel, and weighted effort – were selected for the simulation study because they are representative of existing large-scale monitoring programs that balance some combination of targeted, surveillance, and landscape monitoring (Eyre et al. 2011). For all designs, we defined *site* as the sampling location within a *unit*, the local spatial area (e.g., park, reserve, etc.), and *region* as the overall geographical extent encompassing all of the local units. The monitoring designs vary in their allocation of effort across units to evaluate status, trends, and drivers of population and community change within a defined region. Below, we describe each design, including pros and cons of the various approaches.

The "stratified random design" makes use of an approach in which a fixed percentage of sites randomly selected from each unit (weighted by the number of sites available at each unit) are surveyed periodically, usually annually (Thompson 2012). For example, the North American Breeding Bird Survey uses a uniform number of randomly selected sites (i.e., routes) for each one degree of latitude and longitude block in every US state (and parts of Canada and Mexico), which are targeted for annual sampling (Ziolkowski et al. 2010, Sauer et al. 2013). Stratified random sampling designs are intended to provide information on each unit, including the status, trends, and drivers of monitored populations or communities, although the precision of inferences depends on the number of sites monitored in each unit.

The “weighted effort design” is an approach in which all relevant units are available for sampling, however sampling effort is unevenly distributed across units each year (i.e., intense monitoring of sites at a subset of units, limited monitoring of sites at the remaining units). For example, amphibian monitoring of National Parks in the National Capital Region Inventory & Monitoring Network (National Park Service 2005) conducts a disproportionate level of replicate visits at select parks that have a long history of or higher need for monitoring (Wright et al. 2020b). This design incorporates elements of the stratified random design described above, but also distributes effort to provide a more granular perspective at a subset of units. Thus, its ability to estimate parameters for units is not equitable in a region; high accuracy and precision of parameter estimates is achieved in some units at the expense of others in the region.

The “indicator design” is an approach in which a subset of units, which are selected to represent political or biological domains, are surveyed intensively while remaining available units are not sampled at all. The National Science Foundation’s Long-Term Ecological Research (LTER) Network is an example of this approach, as 28 representative units (of specific landscape types) across the United States are monitored intensely through time (Callahan 1984). This approach ensures robust temporal coverage within each unit, but limited spatial replication. The indicator unit design assumes that relevant parameter estimates of the indicator units are indicative of similar unmonitored units, that the relationship between monitored and unmonitored units is known and constant over time, and/or that parameter estimates at unmonitored units are not of central interest.

The “rotating panel design” is a spatio-temporal varying design in which units are surveyed at specific, rotating intervals (McDonald 2003, Dobbie et al. 2008). For example, within the Alberta Biodiversity Monitoring Program, every available site across the province is sampled once each five-year period on a rotating basis (Stadt et al. 2006), ensuring extensive spatial coverage at the expense of limited temporal replication. The rotating panel design allocates some degree of monitoring effort in all units across the temporal extent of the monitoring program, ensuring high spatial coverage and representation across the region. However, temporal coverage is minimal because repeated visits to individual units occur infrequently.

The “split panel design” is a spatio-temporal varying design in which a set of core units are consistently monitored over time while the remaining set of units are monitored on a variable or rotating basis (McDonald 2003, Dobbie et al. 2008). The National Ecological Observatory Network (NEON) uses this approach with a set of established study areas that are fixed and sampled every year as well as relocatable units that can be moved every 5–10 years (Kao et al. 2008, Keller et al. 2008, Thorpe et al. 2016). This design integrates elements of both the indicator and rotating panel strategies, attempting to alleviate the limited spatial coverage of the indicator design and the limited temporal coverage of the rotating panel design. As such, it emphasizes intensive monitoring at a select number of units across time while also attempting to achieve broader spatial coverage.

Data Simulation

To assess the effectiveness of each of the five monitoring designs in estimating species and community status, trend, and driver estimates within and across scales, we simulated 500 datasets for each monitoring design at five sampling effort levels, defined as the percentage of sites in the region sampled (10%, 20%, 30%, 40%, 50%) for a total combination of 25 simulation scenarios and 12,500 unique datasets (Appendix A). For each dataset, we simulated 10 years of multi-species occupancy data (25 total observed species, though this varies by unit and simulation) across 10 hypothetical spatial units. The number of available sites in each spatial unit was randomly drawn from a uniform distribution with a minimum bound of 10 sites and a maximum bound of 100 sites (16, 21, 23, 35, 40, 47, 66, 72, 90, 98). We chose 10 units (and the corresponding number of sites at each unit) to closely resemble the network of monitoring units in our case study (NCRN, National Park Service 2005). Administrative evaluation is typically on 5-year cycles in U.S. federal programs, and thus 10 years is a reasonable timeframe for both assessment (sufficient time series for estimation) and enacting management activities (Government Performance and Results Act of 1993).

Datasets were simulated using occupancy and detection parameter estimates from an analysis of the long-term, regional amphibian monitoring data collected in the NCRN (Wright et al. 2020b), which is characterized by a regional amphibian community with low mean detection ($p = 0.3$) and low mean occupancy ($\psi = 0.3$). We assumed moderate heterogeneity (standard deviation of 0.5) across unit-level parameter means (i.e., metacommunity), and moderate heterogeneity (sd of 0.5) across all species-level parameter means (i.e., community). By incorporating a reasonable range of variability in the generation of simulation parameters across runs, there is considerable heterogeneity in the simulation of unit- and species-level parameters, resulting in a much broader parameter space. We categorized covariate effects as moderate $|0.4|$ or strong $|0.8|$. We used the same model to both generate and analyze the latent occurrence state for species and the community (described in full detail below in the *Analysis* section).

Following simulation of the latent occurrence state for all species in all units and sites on 12,500 occasions, we then simulated sampling according to one of the unique monitoring design and sampling effort level combinations (e.g., stratified random design with 10% of sites across the region sampled) to obtain corresponding datasets. We assumed that each site selected for sampling was surveyed on four replicate visits per year (unless otherwise indicated), which is sufficient for detecting declines in occupancy (Field et al. 2005) and consistent with the current protocol in the NCRN. Within each sampling effort level, the total number of sites visited annually within the region across the monitoring designs was consistent which ensured that our results were comparable. Thus, designs only differed in which sites, across spatial units, were sampled, not in how many total sites were sampled at the regional level.

To implement sampling in the stratified random design, the same proportion of randomly-selected sites at each unit, relative to each effort level, was sampled continuously for all ten years (Table B.1). For the weighted effort design, all units were sampled similar to the stratified random design, however, the number of replicate visits per site in each year varied among units (6 replicate visits for sites in half of the units, and 2 for the remaining half of units; Table B.1). For the indicator design, the same random sample of sites at a subset of units (containing half of all available sites across the region) was sampled every year (Table B.2). For the rotating panel design, two sets of units containing an equal number of randomly selected sites were sampled on alternate two-year rotations (Table B.3). For the split panel design, the same random sample of sites at a subset of units (containing half of all available sites across the region) was sampled every year, while the remaining units were split into two equal sets that were surveyed on alternate two-year periods (Table B.4).

Analysis

Multi-species (community) occupancy models are often used in the analysis of biodiversity monitoring data to estimate richness as well as species and community dynamics (Dorazio and Royle 2005, Dorazio et al. 2006). These models utilize replicate observations to incorporate detection probability (p) in the estimation of the true latent state of species occurrence (present or absent) at a sampling site (MacKenzie et al. 2002). By incorporating detection and also assuming a shared link across species within a community, multi-species occupancy models can accommodate data from rare, cryptic, and unobserved species to produce accurate estimates of individual species occupancy probabilities (ψ) and species richness (Boulinier et al. 1998, Zipkin et al. 2010). The recent development of multi-region community occupancy models incorporates both multiple species and multiple independent spatial units through a unified statistical analysis (Sutherland et al. 2016), allowing for the investigation of community occupancy dynamics across spatial scales (e.g., ranging from local to regional levels).

We fit a multi-region community occupancy model (Sutherland et al. 2016, Wright et al. 2020b; Appendix C) to each simulated dataset to evaluate how the estimated parameters compared to the true parameter values for each of the 25 allocation strategies (five designs at five effort levels) using the same biological process model that was used to generate the data. We summarized the data into an array, $X_{i,r,j,t,k}$, with the detection ($X_{i,r,j,t,k} = 1$) and nondetection ($X_{i,r,j,t,k} = 0$) histories for each species *i* within unit *r* at site *j* during year *t* on replicate k. We assumed the detection of a species was conditional on the presence of species i within unit *r* at site *j* during year *t* ($Z_{i,r,j,t} = 1$ if the species was there and a structural 0 otherwise) and the probability of detecting species i within unit r at site j during year t on replicate k ($p_{i,r,j,t,k}$) according to a Bernoulli process:

$$X_{i,r,j,t,k} \sim Bernoulli(Z_{i,r,j,t} * p_{i,r,j,t,k}).$$

We then modeled detection probability assuming that detection could change by species or unit where: $logit(p_{i,r,j,t,k}) = \beta_{i,r}$, in which $\beta_{i,r}$ is an intercept term indicating the detection probability for each species i in each unit r on the logit scale.

We similarly modeled species occupancy state, $Z_{i,r,j,t}$, with a Bernoulli random process:

$$Z_{i,r,j,t} \sim Bernoulli(\psi_{i,r,j,t}),$$

where $\psi_{i,r,j,t}$ is the occupancy probability of species i within unit r at site j of year t. We incorporated covariates on species occupancy probability using a logit link function:

$$logit(\psi_{i,r,j,t}) = \alpha 0_{i,r} + \alpha 1_{i,r} * Year_t + \alpha 2_{i,r} * Site\ Covariate_{j,r} + \alpha 3_{i,r} * Z_{j,t-1,i,r}.$$

We included species- and unit-specific intercept terms for mean occupancy ($\alpha 0_{i,r}$), and effects for year ($\alpha 1_{i,r}$), a spatially varying covariate ($\alpha 2_{i,r}$), and an autologistic process ($\alpha 3_{i,r}$). The covariate that influences species occupancy probabilities ($Site\ Covariate_{j,r}$) varies by sites and was randomly generated during the data simulation process (from a normal distribution with a mean of 0 and a standard deviation of 1). The autologistic term incorporates the processes of colonization (when $Z_{j,y-1,i,r} = 0$) and extinction (when $Z_{j,y-1,i,r} = 1$) that drive occupancy patterns for many species, including amphibians (Dorazio et al. 2010, Zipkin et al. 2012).

We categorized ‘status’ as mean occupancy ($\alpha 0$, the spatial distribution of occupancy in a moment of time), ‘trend’ as the effect of year ($\alpha 1$, the increase or decrease of occupancy over time), and ‘drivers’ as the effects of the spatially varying covariate ($\alpha 2$) and the autologistic process ($\alpha 3$, the underlying processes that can influence occupancy status and trend). To link the single-species occupancy models at a community level, we assumed that each parameter was drawn from a common unit-level normal distribution (e.g., $\alpha0_{i,r} \sim Normal(\mu_{\alpha0,r}, \sigma^2_{\alpha0})$), and each unit-level distribution was drawn from a common region-level normal distribution ($\mu_{\alpha0,r} \sim Normal(\bar{\mu}_{\alpha0}, \bar{\sigma}^2_{\alpha0})$), matching the data generation process. This allowed us to estimate and compare parameters at both the unit (e.g., for status: $\mu_{\alpha0,r}$) and region (e.g., for status: $\bar{\mu}_{\alpha0}$) levels.

We ranked the five monitoring designs in terms of their abilities to accurately and precisely recover estimates of the status, trend, and driver parameters across the two spatial scales: for local units individually and the region collectively. We calculated the root mean square error (RMSE) for all parameters in each monitoring design and sampling effort level combination to evaluate differences between parameter values used to simulate the data and those estimated by the model. We estimated the parameters in our models for each simulated dataset using a Bayesian framework in R (R Core Team 2016) with the program JAGS and corresponding 'jagsUI' package (Plummer 2003, Kellner 2015; see Appendix A and Appendix C). We set vague priors for each parameter: mean regional-level intercept parameters for occupancy ($\bar{\mu}_{\alpha0}$) and detection ($\bar{\mu}_{b0}$) had normal prior distributions with a mean of 0 and a variance of 2.70 (Lunn et al. 2012), and variance parameters with gamma prior distributions with shape and scale parameters of 0.1. The mean regional-level slope parameters (e.g., $\bar{\mu}_{\alpha1}$) had normal prior distributions with a mean of 0 and a variance of 10, and similar prior distributions for the variance term as the intercept parameters. Convergence for each parameter was assessed using the Gelman and Rubin convergence diagnostic ($\hat{R}$ statistic < 1.1; Gelman & Rubin 1992, Gelman & Shirley 2011).

Results

Status

At the regional level, the stratified random design had the lowest RMSE in estimating mean community-level occupancy ($\bar{\mu}_{\alpha 0}$) across all effort levels, followed closely by the split panel design (average RMSE was 2% higher compared to the stratified random design), rotating panel design (6%), and the weighted-effort design (13%), with the indicator unit design performing much more poorly than the other four approaches (290%; Table 2.1). For the stratified random design, RMSE decreased with increased effort (by as much as half when going from 10% to 50% effort), however, the gains were substantially larger when the effort was low (i.e., a change from 10% to 20% effort yielded more improvement than a change from 40% to 50% effort). Across sampling designs, the relative decrease in RMSE was tempered as effort increased, indicating a general decrease in returns of estimation bias and accuracy for the higher effort levels. The differences in RMSE across monitoring designs were most pronounced when effort was low (Fig. 2.1a), indicating that the differences in performance among monitoring designs diminish as effort is increased.

At the unit level, the stratified random design again had the lowest mean RMSE (across all units) in estimating the mean occupancy across species within a unit ($\mu_{\alpha 0,r}$) for the individual r units across all effort levels, and the lowest variation of RMSE across all units in each effort level (Fig. 2.1b, Table 2.1). However, while the mean and variance were low, the lower bound of unit-level RMSE values was highest in the stratified random design (RMSE = 0.126), as compared with the weighted (0.117), rotating panel (0.120), split panel (0.120), and indicator unit designs (0.110). Thus, while stratified random design provided the most equitable estimates across all units in a region, other designs resulted in more accurate and precise estimates of some individual units at the expense of parameter accuracy and precision in other units (Table 2.1). The importance or significance of individual units may vary according to management or monitoring objectives, and equitability in parameter accuracy or precision across units may not be necessary in every monitoring scenario.

Trends

Unsurprisingly, monitoring design performance for estimating trends at the regional level were similar to those for estimating status. The stratified random design had the lowest RMSE in estimating a linear year effect on occupancy ($\bar{\mu}_{\alpha 2}$) across effort levels (Fig. 2.1c), followed closely by the weighted effort design (average RMSE was 3% higher compared to the stratified random design), split panel design (6%), rotating panel design (9%), and lastly the indicator unit design (350%, Table 2.1). For the stratified random design, RMSE decreased by 17% when effort was increased from 10 to 20%, 20% when effort was increased to 30%, 28% when effort was increased to 40%, and 29% when effort was increased to 50% (Fig. 2.1c). Other designs showed a similar plateau of increased precision and accuracy as effort increased.

At the unit level, the stratified random design again had the lowest mean RMSE in estimating the year effect parameter ($\mu_{\alpha 2,r}$) across all effort levels, and the lowest variation of RMSE across all units in each effort level (Fig. 2.1d, Table 2.1). However, while RMSE estimates per unit were more equitable for the stratified random design, the lower bounds of the unit-specific RMSE distributions for the other four designs were again less than that of the stratified random design. Of those other designs, the indicator unit and rotating panel designs had the lowest individual unit-specific RMSE estimates (0.102, Table 2.1). This again reveals that while the stratified random design performs better for average trend estimates, the other designs are capable of estimating trends more accurately and precisely for a subset of units.

Drivers

Our results on drivers differed somewhat from the status and trends parameters. At the regional level, the rotating panel design had the lowest RMSE in estimating the effect of a site-specific covariate on occupancy ($\bar{\mu}_{\alpha 1}$) across effort levels (Fig. 2.1e), which was comparable to estimates for the split panel design (average RMSE was < 1% higher compared to the rotating panel design), and then followed by the stratified random design (8%), weighted effort design (11%), and the indicator unit design (313%, Table 2.1). Similarly, at the unit level, the rotating panel design had the lowest mean RMSE in estimating the spatially-varying covariate parameter ($\mu_{\alpha 1,r}$) across all effort levels, and the lowest variation of RMSE across all units in each effort level (Fig. 2.1f, Table 2.1). However, again, the lowest individual unit RMSE estimate was from the indicator unit design.

In estimating the autologistic effect on occupancy ($\bar{\mu}_{\alpha 3}$) at the regional level, the stratified random design had the lowest RMSE across effort levels (Fig. 2.1g), followed by the weighted effort design (average RMSE was 16% higher compared to the stratified random design), split panel design (19%), rotating panel design (33%), and then the indicator unit design (234%, Table 2.1). Likewise, at the unit level, the stratified random design had the lowest mean RMSE in estimating the autologistic slope parameter ($\mu_{\alpha 3,r}$), and the lowest variation of RMSE across all units in each effort level (Fig. 2.1h, Table 2.1). However, both the indicator unit and weighted effort designs had lower individual unit RMSE estimates (0.148 and 0.155, respectively) relative to the stratified random design (0.171).

Discussion

Our results suggest that stratified random sampling remains the most precise, accurate, and efficient monitoring approach for understanding wildlife occupancy at multiple spatial scales. With the exception of the spatially-varying parameter on occupancy ($\alpha 2$), the stratified random design consistently had the lowest RMSE estimate across parameters at the regional level, and the lowest mean and variation of RMSE estimates at the unit level. This is not unexpected and, indeed, one of the reasons that stratified random sampling is so widely used. A stratified random design ensures that data come from a representative sample that accounts for spatial heterogeneity, leading to an efficient use of monitoring effort (Schreuder et al. 2004). Further, stratified random sampling avoids subjective decision making, and potential biases, in site or unit representation in a monitoring program (Dobbie et al. 2008). Despite its many advantages, other monitoring designs may be preferable if inference across parameters or scales is not a primary goal of a monitoring program. For example, the rotating panel design outperformed all other designs in estimating the site-specific effect, suggesting that the optimal choice of monitoring effort depends on the parameters of interest to managers. While the other designs (rotating panel, split panel, and weighted effort) had higher RMSE values relative to the stratified random design for most parameters, that difference was marginal in many instances (i.e., < 15% difference in RMSE; Table 2.1), particularly when effort was high. Additionally, the stratified random design had the lowest mean and variation of unit-level estimates but other designs typically performed better for individual units (most consistently the indicator unit design; Table 2.1). Thus, the optimal design for data collection depends on the monitoring objectives and spatial scale of interest and there will necessarily be trade-offs in parameter accuracy and precision (Fig. 2.2).

Our analyses were motivated by our work with the NCRN Inventory and Monitoring program of the U.S. National Park Service. The NCRN 'Vital Signs' monitoring program seeks to provide an understanding of the condition of National Parks in the Washington, D.C. metropolitan area, and identify appropriate management actions necessary to maintain natural resources in the network of parks (Fancy et al. 2009). As the program considers optimal monitoring strategies to meet their objectives and budget constraints, we aimed to evaluate the effectiveness of multiple proposed monitoring designs to inform one of their key Vital Signs, amphibian occurrence and distribution (National Park Service 2005). For the NCRN, and other hierarchically-organized systems, the stratified random monitoring design performs best across their primary objectives of understanding the status, trends, and drivers of amphibian occurrence at individual parks and across the network. However, the optimal allocation of monitoring resources must also consider whether equal precision is needed at all parks (i.e., units), which may not be the case for decision-making. For example, parks with amphibian populations near an ecological or management threshold (Martin et al. 2011) may require increased precision when deciding whether to implement management interventions. While the stratified random design did perform marginally better than the weighted effort design at the regional-level (and across the average of unit-level estimates), the weighted effort design had a lower bound to unit-specific estimates across all four parameters. Thus, the selection of an optimal monitoring design will depend on the need of information across scales and among individual parks in the network. Importantly, we found that the return on monitoring investment was not linear, meaning that the magnitude of increase in precision and accuracy declined as additional sites were sampled. While our results provide valuable information concerning the trade-offs of different sampling designs applicable to real-world decision making (e.g., in the NCRN and other hierarchically structured amphibian networks), these results are also generalizable as the parameter space we use is relevant to a variety of taxa and systems (Sanderlin et al. 2014, Sutherland et al. 2016).

Monitoring objectives and constraints will vary across programs, and thus a balance of scale and/or parameters of focus may not always be necessary, beneficial, or efficient. Here, we evaluated the performance across three parameter estimates common to published monitoring programs—status, trends, and drivers—at two management-relevant scales to identify and understand tradeoffs that might arise in large-scale and long-term monitoring programs. Although we demonstrated that the stratified random design is preferable in most cases, real-world factors may support the implementation of other sampling designs. For example, if information is needed primarily to understand drivers of species distributions across space, a hypothesis-based approach (Nichols and Williams 2006) that emphasizes spatial replication and increased sample size may be preferential. In this case, the rotating panel design, which sacrifices temporal replication (across years) for an increased number of sites, may be the preferred design. However, this design choice would limit the ability of the monitoring program to detect and respond to declines as they arise.

The importance of information for individual management or governance units (e.g., refuges, states, etc.) may not be equal across a broad geographical extent. This can occur when the system at an individual unit is far from the decision or management threshold or the decision at that unit is insensitive to the system state (Martin et al. 2012). The stratified random design had the lowest mean and variation among RMSE estimates across all units, but other designs had lower bounds to the RMSE estimates at the unit level (e.g., Fig. 2.1b). In cases in which regional-level estimates are of lesser importance relative to management objectives at select units, designs such as the weighted effort or split panel, in which a subset of the units receive a disproportionate amount of effort, may be preferred. Selection of one of those two designs will vary depending on the focus of the monitoring program: the weighted effort design better captured temporal variation (e.g., trend and autologistic effect) whereas the split panel design better captured spatial variation (e.g., status and site-specific effect; Fig. 2). Further, not all large-scale monitoring programs are meant to extrapolate findings to a broader spatial extent. For example, the NSF LTER network is designed to provide highly detailed information to understand long-term ecological phenomena at spatially independent locations (Callahan 1984). In such cases, when the regional-level estimates are not of primary importance, the indicator unit design, in which resources are targeted at select units instead of balancing at the regional level, may be most efficient.

Evaluating monitoring program designs is important as we seek to understand, manage, and conserve the world's ecosystems. The use of evidence-based decision making to guide the design and objectives of large-scale monitoring programs is necessary to ensure justification and accountability of relevant information-gathering investments (Wintle et al. 2010). There are a number of considerations in designing and implementing effective programs aimed at monitoring biological communities across spatial scales (Olsen et al. 1999). Past research has focused on developing monitoring approaches that account for observation biases (MacKenzie and Royle 2005, Guillera-Arroita et al. 2010), spatial variation in species distributions and/or abundance (Pollock et al. 2002), and species rarity (Pacifici et al. 2012, Sanderlin et al. 2014). However, less research has focused on dealing with monitoring objectives that differ across and within scales in a collaborative monitoring network. Our results help inform the trade-offs of various monitoring objectives under fixed budgets in such multi-scaled systems. However, adjusting the design of large-scale monitoring programs may be logistically challenging or infeasible. Thus, optimizing the data collection process may not always be the appropriate response. With increased access to data from other monitoring programs, various research labs, and citizen science initiatives, future research that leverages integrative analyses and multiple data sources (e.g., integrated population models) can further enhance existing and future monitoring programs (Saunders et al. 2019, Zipkin et al. 2021).

Only 25% of the necessary budgets to implement threatened species recovery plans in the United States is allocated annually (Gerber et al. 2016). Approximately half of the recovery resources are dedicated to research and monitoring—not on-the-ground management actions (Buxton et al. 2020). Hence, increasing the efficiency of monitoring programs has the potential to free up resources for management activities. At the center of this issue is *how* to most efficiently use available resources (e.g., targeted vs. surveillance monitoring; Nichols and Williams 2006, Wintle et al. 2010). Careful consideration of the management context, objectives, and specification of desired accuracy and precision of various parameters can help achieve the objectives of large-scale monitoring programs that aim to inform and guide science, management, and policy at multiple scales.

Table 2.1: Comparison of root mean square error (RMSE) estimates for each monitoring design and parameter of interest. RMSE values are summarized across effort levels. Region-level estimates for RMSE were characterized for the regional mean parameter (e.g., for status: $\bar{\mu}_{\alpha 0}$). Unit-level estimates were characterized for the unit mean parameters (e.g., for status: $\mu_{\alpha 0,r}$) and include: the average RMSE of all units and the lower and upper bounds (in parentheses) of the distribution of unit-level RMSE estimates for each parameter.

Monitoring Design & Scale	Parameter of Interest			
	Status	Trends	Drivers	
	Mean Occupancy	Year-specific effect	Site-specific effect	Autologistic effect
	$\alpha 0$	$\alpha 1$	$\alpha 2$	$\alpha 3$
Stratified Random				
Region	0.0607	0.0477	0.0593	0.0800
Unit	0.155 (0.126–0.197)	0.128 (0.110–0.159)	0.152 (0.112–0.231)	0.223 (0.171–0.301)
Weighted Effort				
Region	0.0684	0.0491	0.0605	0.0929
Unit	0.175 (0.117 – 0.257)	0.135 (0.108 – 0.169)	0.159 (0.109–0.251)	0.248 (0.155–0.338)
Indicator Unit				
Region	0.177	0.168	0.171	0.187
Unit	0.348 (0.110–0.568)	0.336 (0.102–0.560)	0.337 (0.0999–0.556)	0.377 (0.148–0.566)
Rotating Panel				
Region	0.0643	0.0518	0.0547	0.106

Table 2.1 (cont'd)

Unit	0.162 (0.120–0.203)	0.136 (0.102–0.182)	0.143 (0.111–0.190)	0.268 (0.182–0.344)
Split Panel				
Region	0.0619	0.0505	0.0550	0.0955
Unit	0.159 (0.120–0.206)	0.135 (0.106–0.186)	0.147 (0.110–0.212)	0.248 (0.175–0.336)

Figure 2.1: Estimated root mean square error (RMSE) for each monitoring design and effort combination for each parameter at the regional scale (a, c, e, and g). The unit-level RMSE estimates are organized by individual units (dots) and box plots describing the distribution of RMSE values across the units (b, d, f, and h). The Indicator Unit design is not shown as its RMSE values were much higher than the others (see main text).

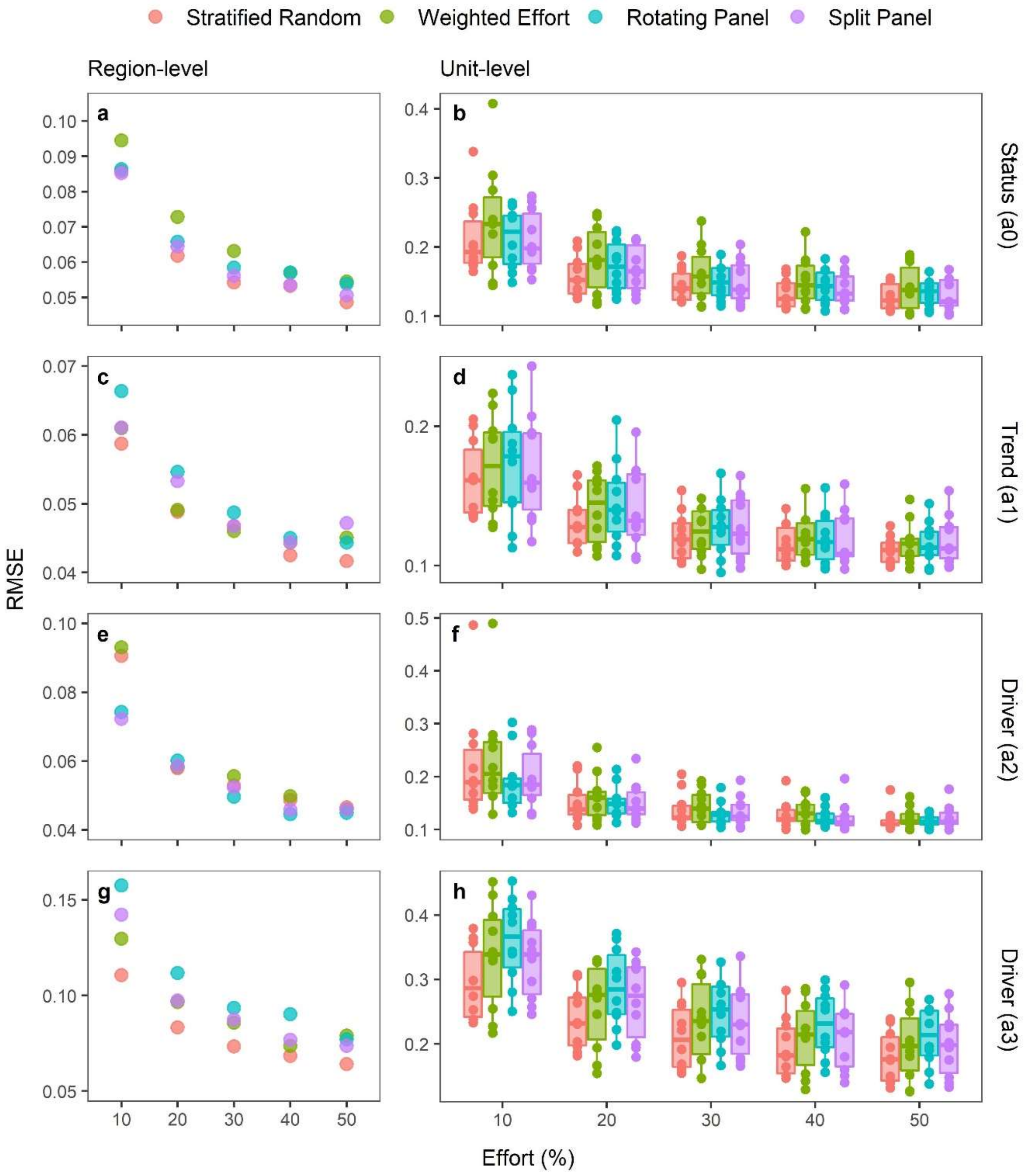
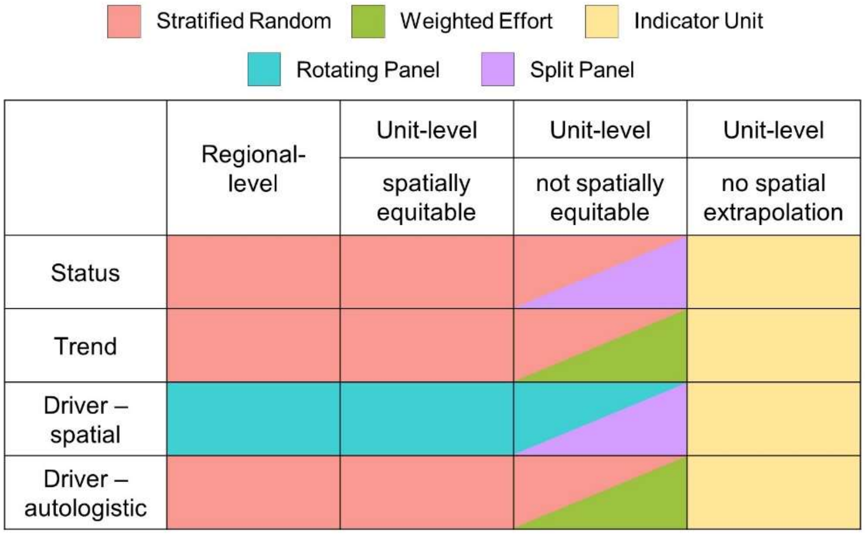


Figure 2.2: The recommended monitoring design(s) for each spatial scale, objective, and parameter combination. Recommendations were determined by which design(s) had the lowest root mean square error (RMSE) estimates within the simulation study. Parameters evaluated were: $\alpha0$ (mean occupancy) for *Status*, $\alpha1$ (year-specific effect) for *Trend*, $\alpha2$ (site-specific effect) for *Driver – spatial*, and $\alpha3$ (autologistic effect) for *Driver – autologistic*. Parameters were assessed at the regional (e.g., for status: $\bar{\mu}_{\alpha0}$) and unit (e.g., for status: $\mu_{\alpha0,r}$) levels.



🟥 Stratified Random
🟩 Weighted Effort
🟨 Indicator Unit
🟦 Rotating Panel
🟪 Split Panel

	Regional-level	Unit-level	Unit-level	Unit-level
		spatially equitable	not spatially equitable	no spatial extrapolation
Status	🟥	🟥	🟥 🟪	🟨
Trend	🟥	🟥	🟥 🟩	🟨
Driver – spatial	🟦	🟦	🟦 🟪	🟨
Driver – autologistic	🟥	🟥	🟥 🟩	🟨

CHAPTER 3: PRIORITIZING BIODIVERSITY MANAGEMENT ACROSS NETWORKS OF PROTECTED AREAS

Abstract

Biodiversity is declining rapidly despite ambitious global targets to mitigate impacts of anthropogenic-induced change on biodiversity. The lack of progress on this issue is partly due to the complex decision-making contexts that necessitate a multi-scaled approach to design and implement conservation management. This complexity arises because the scope and scale of environmental challenges encompasses multiple decision makers across discrete and/or overlapping management units. Here, we applied a multi-scaled modeling and decision framework to a case study focusing on amphibian biodiversity across a network of national parks. Amphibian communities were found to be declining at 8 of 9 monitored parks within the region and thus management is needed to mitigate these losses and reverse species trajectories. Using data from a long-term regional monitoring program, we predicted changes in amphibian species richness following a management intervention designed to increase richness at individual wetlands within parks. To quantify the multi-scale decision contexts, we used a sensitivity analysis to compare different allocations of management resources across parks to balance objectives at both local and regional levels. We included objective weights that quantify how decision makers value the conservation of amphibians at each scale, and how they value their goals relative to the goals of decision makers at different spatial units and scales (i.e., collaboration). We found that the impacts of the management intervention (increase in wetland hydroperiod) vary from park to park. Further, we found that the prioritization of wetlands to manage across the region, and the resulting increase in wetland-specific species richness, varied

depending on the unique combinations of conservation and collaboration objective weights at each scale. More broadly, our results demonstrate the importance of balancing trade-offs in local and regional objectives to collaboratively address biodiversity declines at multiple spatial scales and provide a path forward for successful implementation of conservation management.

Introduction

Failure to reach global biodiversity targets stems in part from the conservation management required to protect biodiversity across space is increasingly interrelated, complex, and difficult (Cash et al. 2006, Game et al. 2013, Díaz et al. 2019, Leclère et al. 2020). Threats to biodiversity, such as land use and climate change, are broad but also multi-scaled (Heffernan et al. 2014)—requiring the coordination of management actions across geographic scales (Dietz et al. 2003, Armsworth et al. 2015). While ambitious goals and policies to mitigate biodiversity loss are typically set at continental or even global scales (e.g., Convention on Biological Diversity 2010), decisions are often made locally (Stewart et al. 2013). Resource management decisions may vary because of geographic variation in types and intensity of threats (e.g., Richgels et al. 2017), responses of local biodiversity to management (Muths et al. 2017, Grant et al. 2020), and local stakeholder values (McDaniels et al. 2006, Robinson et al. 2016). As a result, land management is often fragmented by geography, organization, and policy (Lubbel 2013, Tallis et al. In Review).

Coordination of the management needed to achieve large-scale goals is hindered by the fragmented jurisdictions of management entities within a governance network (Lubbel 2013, Michaels & Tyre 2012). Effectively executing a conservation decision requires the legal or regulatory authority to make a decision, the power to carry out a decision, and the resources needed to implement related actions. In the context of landscape conservation, these components are often distributed unevenly across different organizations, administrative levels, or geographic locations, requiring collaboration across multiple decision makers to meet landscape objectives (Ostrom 2010). For example, while federal or regional agencies may have some central organizing authority, individual resource managers may have differential power to make or implement decisions within protected areas under their jurisdiction, while the resources needed for successful conservation may come from a mixture of national, regional, and/or local budgets. Without recognizing and navigating such complexities of collaborative landscape conservation, desired conservation outcomes may not be realized at scales relevant to biodiversity.

Incorporating a multi-scaled approach to conservation decision making and implementation can lead to more effective management than if the hierarchical structure of governance and management is ignored (Cash et al. 2006). Policy and management decisions are recommended to reflect the scale and structure of the target ecological processes and governance systems (Crowder et al. 2006, Gunderson et al. 2016, Wright et al. 2020a). Multi-scaled approaches can allow for achievement of large-scale goals while simultaneously framing the local decisions that need to be made with respect to varying constraints, objectives, and uneven resource distribution. Collaboration steeped and strengthened by shared objectives, or recognition of where objectives, needs, and constraints differ within and across scales, can facilitate the optimal allocation and coordination of resources for effective landscape conservation (Reed et al. 2016, Scarlett & McKinney 2016, Berardo & Lubbell 2019).

We outline a process that is designed to understand, predict, and then prioritize management across a multi-scaled governance network. Specifically, the analytical steps in this process include the (1) analysis of existing data to *understand* system dynamics across ecological scales, (2) *prediction* of changes to the system following management interventions, and (3) *prioritization* of management across the system relative to stakeholder objectives at different scales of governance. Guidance on the implementation of steps one and two across scales are well documented in the literature (e.g., Heffernan et al. 2014, Tallis et al. In Review); however, the third step is perhaps the most challenging to implement in multi-scale management problems. Thus, we specifically evaluate how to prioritize management across scales by incorporating discrete value weights on the conservation and collaboration goals at each relevant decision-making scale.

We apply this analytical process to a case study to improve the status of the amphibian community in the National Capital Region Network (NCRN) of the National Park Service (NPS), a network of national parks in the Mid-Atlantic region of the United States (NPS 2005). Previous work has demonstrated the desire in the NCRN to maximize mean wetland-specific richness of amphibians, which is considered a ‘vital sign’ within the region as an important natural resource (NPS 2005, Grant et al. 2013). A recent synthesis of monitoring data demonstrated that hydroperiod (the length of time a wetland holds water and is available for amphibian development) is a major determinant of wetland occupancy and species richness of amphibians within national parks in the NCRN (Zipkin et al. 2012, Wright et al. 2020b). Wetland hydroperiod is also among the most feasible amphibian population and habitat attributes for park managers to modify without disturbing other natural and cultural resources in the parks (Grant et al. 2013). Thus, increasing the hydroperiod of individual wetlands has been identified as a potential approach to increase mean wetland richness given available resources and constraints.

Our objective is to evaluate the optimal allocation of resources across space to maximize mean wetland-specific amphibian richness in this multi-scaled governance network—balancing both local and regional needs, constraints, and objectives. To do this, we first fit a multi-region community occupancy model to data from the long-term, regional amphibian monitoring program in the NCRN. Next, we use parameter estimates from the model to predict the improvement in the conservation objective (wetland-specific species richness) following management intervention (increase in hydroperiod) of individual wetlands within each of the parks. Finally, we use a sensitivity analysis to demonstrate how to prioritize wetlands for management across the region relative to different weights of the conservation and collaboration objectives at local (individual parks) and regional (the entire network of parks) scales. Our results provide a framework for a regional network of national parks to mitigate amphibian declines. More broadly, our study provides insight into approaches to balance the needs, constraints, and objectives of biodiversity conservation across multiple scales in collaborative landscape conservation.

Methods

The Northeast Amphibian Research and Monitoring Initiative collects data on the occurrence of wetland-breeding species in individual wetlands (hereafter, occupancy data) at 9 of 11 national parks throughout the NCRN. Each year, field crews conduct repeat surveys of (randomly selected) monitored wetlands throughout the breeding season and record the detection (or not) of individual species. See Mattfeldt et al. (2009) for the initial design of the monitoring program and Grant & Brand (2012) for full sampling protocols.

We fit a multi-region community occupancy model (Sutherland et al. 2016, Wright et al. 2020b) to the monitoring data collected between 2005-2020 to estimate individual species dynamics as well as community and metacommunity richness patterns. This hierarchical modelling approach allowed us to incorporate imperfect detection of species throughout the sampling season and to include data-deficient species and parks in our analyses. We categorized the hydroperiod of each wetland (the length of time that a wetland holds water) as temporary (dries up annually during the summer), semi-permanent (dries up every few years), and permanent (never dries) and then incorporated this categorical covariate in our occupancy model. We included other sources of environmental variation (i.e., annual wetland area, annual wetland conductivity, and wetland connectivity, which is fixed from year to year) on the occurrence probability (Ψ) of species *i* at wetland *j* in park *r* during year *y*. We also included a trend effect of year *y* to determine which species and parks have experienced declines and which might therefore be at risk for future declines. For each variable, we model an effect for each species *i* and park *r* combination:

$$\text{logit}(\Psi_{j,y,i,r}) = \alpha 0_{i,r,temporary} + \alpha 1_{i,r,hydro_j} * \text{hydroperiod}_j + \alpha 2_{i,r} * \text{area}_{j,y} + \alpha 3_{i,r} * \text{connectivity}_j + \alpha 4_{i,r} * \text{conductivity}_{j,y} + \alpha 5_{i,r} * \text{trend}_y \,.$$

We included a day of year covariate within the observation component of the model (Wright et al. 2020b). Species-specific parameters at each park are linked at the community level, e.g., $\alpha 5_{i,r} \sim Norm(u_{\alpha 5,r}, \sigma^2_{\alpha 5,r})$, and each park community is linked together at the metacommunity level for the region, e.g., $u_{\alpha 5,r} \sim Norm(\bar{u}_{\alpha 5}, \sigma^2_{\alpha 5})$. We calculated a derived parameter of annual wetland-specific richness, $N_{j,y,r}$, by summing the latent occurrences of all species at each sampled wetland *j* for each year *y* from 2005-2020 in all parks. We estimated the parameters in the model using a Bayesian approach with the software R and JAGS (see Appendix D for full model and implementation details).

Using the estimated posterior distributions of the species- and park-specific wetland occupancy parameters, we predicted occupancy rates for each species i at wetland j in park r during year y. We made predictions for the five years immediately following the last year of available data (i.e., 2021-2026). For future years, we held the temporally varying covariates (wetland area and conductivity) constant as the mean of the recorded values across the sampling period for wetland j, but we assumed that the trend effect continues. We used estimated occupancy probabilities, Ψ, and whether or not species i is estimated to exist in park r, W, to predict the presence or absence, Z, of each species i at each wetland j in year y for each posterior iteration s in future years:

$$Z_{s,j,y,i,r} \sim Binomial(\Psi_{s,j,y,i,r} * W_{s,i,r}) .$$

We estimated W using a data augmentation parameter Ω_r, the probability that species i is at park r, $W_{s,i,r} \sim Binomial(\Omega_r)$. We summed the latent Z values for all i species at wetland j in year y to project species richness, N, of each wetland in each year at all parks.

We predicted species richness values at wetlands under two scenarios. The first scenario includes management intervention ($N_{j,y,Action}$), where the hydroperiod for each of the temporary wetlands (241 temporary wetlands in the NCRN out of total of 296 monitored wetlands) is manipulated to semi-permanent. The second scenario uses a 'business as usual' approach (BAU; $N_{j,y,,BAU}$) that assumes the wetland hydroperiod is unchanged (Tallis et al. In Review). We then calculate the net impact, I, to species richness from the action on wetland j in year y:

$$I_{j,y} = N_{j,y,Action} - N_{j,y,BAU} .$$

Note that $I = 0$ for any wetland *j* that was semi-permanent or permanent to begin with (because there is no management intervention and thus no change to species richness). The average difference for expected richness of each wetland *j* is calculated across all posterior distribution iterations to estimate the mean impact of management at each wetland. We assumed that the management intervention occurs immediately after the last year of available data (i.e., following the 2020 sampling season), and that the effects of increasing a wetland's hydroperiod are immediate and durable (i.e., management is implemented perfectly and the effects last the duration of the prediction interval). Thus, when comparing the impacts of management on species richness, we only focused on those impacts in the first year (2021).

We then prioritized wetlands for management intervention across the region with the objective of maximizing mean wetland-specific species richness at both the unit- (i.e., park) and regional-levels (i.e., network). To do so, we estimated the cumulative value (*V*) of each wetland *j* relative to the expected increase in species richness of wetland *j* with the management intervention (*I*); increasing a wetland's species richness results in an increase in the average species richness at the unit and regional levels, the effect of which depends on the value of the increase (i.e., the number of species expected to be gained via management) and the number of wetlands at each level. In addition to the net impact at wetland *j*, we also included terms describing how managers at each scale value amphibians (w_{region} and w_{unit}; both are ≥ 0.0 and ≤ 1.0) and the relative importance of improving the state of amphibian populations (i.e., increasing wetland-level richness) at the local and regional scales (s_{region} and s_{unit}; sum = 1.0):

$$V_j = V_j^{region} + V_j^{Unit}$$

$$V_j^{region} = I_{j,2021} * w_{region} * s_{region}$$

$$V_j^{unit} = I_{j,2021} * w_{unit_j} * s_{unit_j}$$

$$s_{region} = 1 - s_{unit_j}$$

We incorporated the objective weights at the two relevant decision scales: the extent to which regional decision makers value maximizing mean wetland richness across the region, w_{region}, and the extent that unit (i.e., park) decision makers value maximizing mean wetland richness for their individual management unit, w_{unit}. Objective weights can be interpreted as the proportional value each manager places on amphibians relative to other relevant conservation objectives under their jurisdiction: a value near 1 indicates amphibians are a high priority, while a value near zero indicates amphibians do not influence natural resource management decisions at that jurisdiction. Thus, we can incorporate the relative importance of the conservation objective to each decision maker individually.

Additionally, we incorporated two discrete, spatial discounting parameters to reflect the balance of the importance of these priorities across scales (Perrings & Hannon 2001). First, s_{unit} reflects how much local decision makers value their own local goals relative to the larger, regional goal. This parameter weights the importance of the increase in local species richness of a managed wetland, and the difference from 1 weights the importance of increase in species richness not at the local site, but for the region collectively ($s_{region} = 1 - s_{unit}$). A value of 0.5 for s_{unit} (and thus s_{region} as well) would assume that the local decision maker values the increase in amphibian richness at their park equal to an increase in amphibian richness in the region, whereas a value near one indicates local decision makers only care about goals at their jurisdiction, with a value near zero indicating the opposite. Through this parameterization, we can incorporate the relative importance of broader shared goals to the individual goals of each decision maker.

We evaluated the utility of our approach (and the ranking of wetlands) under multiple scenarios to determine the sensitivity of the prioritization of management to the weights of the multi-scaled objective and spatial discounting parameters. Thus, we used hypothetical values as opposed to actual objectives weights (case specific values can be derived from managers through various elicitation techniques; e.g., Martin et al. 2012). We compared how mean wetland-specific species richness in the region would be altered (by examining the mean impact, I, of the top quarter of wetlands ranked by V) across different values of the local and regional objective weights ranging from 0 to 1 (in increments of 0.1). We evaluated these values under four hypothetical scenarios to examine how variation in local objectives among parks influences the management metric as well. These scenarios assume: (1) the value that individual park managers place on amphibians in their park (w_{unit}) is proportional to the number of wetlands (amount of amphibian habitat) at the park, (2) the value that individual park managers place on amphibians at their park (w_{unit}) is inversely proportional to the number of wetlands at each park, (3) the value of improving the state of amphibian populations at parks relative to the regional goal for individual park managers (s_{unit}) is proportional to the number of wetlands at each park, and (4) the value of improving the state of amphibian populations at parks relative to the regional goal for individual park managers (s_{unit}) is inversely proportional to the number of wetlands at each park. Because we are using hypothetical values, we used a metric (such as the number of wetlands) as an objective approach to distinguishing between different scenarios. By using the weights as proportional and inversely proportional to this metric, we are able to see how these scenarios would differ across the extremes of this metric.

Results

At the regional level, mean species occupancy declined over the time frame of our study (2005–2020) as indicated by a negative trend effect ($\bar{u}_{\alpha 5}$; Mean: -0.76; Credible Interval [CI]: -0.25 – -1.34), indicating a broad decline of amphibian occupancy and species richness across the NCRN (Fig. 3.1). Of the 9 monitored parks in the region, 5 parks had a significant (non-overlapping 95% CI with 0), negative trend for community occupancy, 3 parks had a negative (but not significant) trend, and 1 park had no trend ($u_{\alpha 5,r}$; Table 3.1). At the regional level, the effect (on the logit scale) of hydroperiod classification led to significantly higher species occupancy rates in wetlands with semi-permanent hydroperiod relative to a temporary hydroperiod ($\bar{u}_{\alpha 1,\mathrm{semi}}$; 0.67, 0.11 – 1.24 CI), with all 9 parks demonstrating this community-level effect to varying degrees ($u_{\alpha 1,semi,r}$; Table 3.1). In the final year of sampling (2020), mean wetland-specific species richness for permanent wetlands was 3.82 (2.70 standard deviation [sd]), for semi-permanent wetlands was 2.97 (1.78 sd), and for temporary wetlands was 1.79 (1.26 sd) across all sampled parks in the region.

Of all temporary wetlands that were sampled, 91% are projected to increase in species richness if they were to be altered to semi-permanent, although the magnitude of increases varies by both wetland and park (Fig. 3.1). The mean projected gain (*I*) in species richness per wetland of the top quarter of wetlands is 2.16 (0.45 sd). If all 241 monitored temporary wetlands were managed to become semi-permanent, expected wetland-specific species richness would increase by 0.92 (0.82 sd) for all sampled wetlands in the region. Expected wetland richness would increase by 0.77 (0.92 sd) and 0.54 (0.96 sd) if the top half (if ranked by *I*) and the top quarter of wetlands were managed, respectively (Fig. 3.2). These gains are mostly driven by a single park (Manassas [MANA], Table 3.2 and Fig. 3.1), which had the highest mean difference in species richness between temporary and semi-permanent wetlands (Table 3.1). After Manassas, the prioritization of wetlands by impact becomes more evenly distributed across parks (Table 3.2). If the number of managed wetlands was allocated equally across all parks (ranked by net increase and park), the mean expected gain in wetland specific richness (*I*) would be reduced to 1.03 (0.68 sd) for increasing hydroperiod for the top quarter of wetlands, less than half of what it would be if ranked solely by net impact.

The expected change in species richness due to implementing the management action (*I*) on the top quarter of wetlands is sensitive to the objective and spatial discounting weights at both unit and regional scales that we evaluate, ranging from an increase of 0.42 to 2.16 species per wetland on average across the four scenarios and range of possible values (Fig. 3.3). Higher values for the amphibian objective at the regional level (w_{region}) generally led to higher impacts on mean wetland-specific species richness for the region, whereas higher values for the amphibian objective at local levels (w_{unit}), and the focus on local objectives relative to regional goals (s_{unit}), generally led to lower mean impacts of the highly ranked wetlands (Fig. 3.3). These estimates were also sensitive to whether local goals were proportional or inversely proportional to the amount of habitat (Fig. 3.3), which is to be expected given the differences in impact of management intervention across parks (Fig. 3.1) and the amount of habitat at each park. For example, MANA has a disproportionate amount of wetland habitat, a large amount of temporary wetlands, and the highest impact of wetland management. Thus, when the value local decision makers place on increasing mean wetland-specific species richness (w_{unit}) is proportional (Fig. 3.3a) or inversely proportion to the amount of habitat at each unit (Fig. 3.3b), the net impact of management (*I*) can vary by up to one additional species per wetland (particularly when the value of local goals relative to regional goals is high; s_{unit} is close to 1).

Discussion

A major challenge in landscape conservation is the fragmentation of conservation areas, and landscape decisions, with individual local decision makers. Governance structures that organize these discrete units into a collaborative are believed to improve regional conservation outcomes by organizing efforts to achieve a large-scale objective. Here, we demonstrate how incorporating network governance structure explicitly in the decision analytic process (i.e., the value function) can provide a solution for balancing collaborative landscape conservation goals for amphibian communities within a network of protected areas. Our results show amphibian communities are in decline across the NCRN (at 8 of 9 parks) but that the potential impacts of management intervention differ across the landscape, within and among parks (Fig. 3.1 & Fig. 3.2). Most importantly, our results demonstrate how different weightings of objectives and spatial discounting parameters at both scales impact the prioritization of wetlands for management, and the resulting increase of amphibian richness, across the NCRN (Fig. 3.3). These variable impacts highlight a common tradeoff in conservation management: the decision to distribute resources across parks to meet local-scale goals or the concentration of resources to meet regional goals, which often has the highest absolute impact. This choice can lead to markedly different results for the amphibian community as a whole. Hierarchical governance results in complex decision tradeoffs both within and across scales—but here we demonstrate why it is necessary to transparently and explicitly incorporate that complexity into prioritization of management action when financial resources are often limited.

The NCRN offers a tractable example useful for demonstrating how to balance discrete decision makers with non-overlapping jurisdictions and differential authority in collaborative landscape conservation. Within the NCRN, individual parks make and implement management decisions. Network-level objectives can add structure to address the scale, complexity, and uncertainty of regional and global threats. As a result, network-level objectives can help coordinate the strategic allocation of individual and shared resources to management actions across a collaborative network of individual parks. However, individual park constraints and motivations must be considered to reflect individual park capacity and interest to support these larger-scale objectives. This problem is characteristic of, and universal to, conservation, which is inherently local and collaborative (Wyborn & Bixler 2013). Larger entities often do not, and are not necessarily meant to, act across space – they may set goals to guide individual actors (e.g., Convention on Biological Diversity 2020), enact policy to guide, limit, or review individual actions (e.g., U.S. National Environmental Policy Act of 1969), direct resources across space to support local actions (Armsworth et al. 2020), or implement management actions in discrete locations. Success in landscape-scale conservation is thus an emergent property of the individual actions of multiple decision makers.

Conservation for common and widely distributed natural resources is challenging because the fragmented jurisdiction for management necessitates multiple decision makers and the coordination of a combination of individual and shared resources. How objectives are organized and weighted across scales is relative to the "decision space" for this and other landscape problems (Fig. 3.4). Landscape decision spaces can be organized across two dimensions: the extent that governance (in this context, decision making authority) is centralized and the extent that resources to support or implement actions are centralized. Our case study falls in the "collaborative" spaces – in which conservation objectives need to be considered at multiple scales to efficiently pool or allocate some amount of shared resources. This space is emblematic of cross-boundary conservation issues more broadly (e.g. migratory bird management, wildlife disease management, Great Lakes ecosystem management, etc.), and our results demonstrate the sensitivity of the management prioritization to diverse stakeholders' objectives.

Discounting is a process that incorporates changes in perceived benefits that occur at different points in time (e.g., immediate vs future costs; Frederick et al. 2002). Recent advancements have extended this approach to space by including a distance-decay function in cost-benefit analyses (Perrings & Hannon 2001, Baum & Easterling 2010). While treating distance as a continuous variable may work for individual actors, governance operates at discrete (and often multiple) spatial scales and not just continuously across space. Previous research has provided a solution to a spatially nested resource allocation decision with multiple discrete spatial scales (Armsworth et al. 2020). However, their problem assumes that decision making is centralized within a single authority—and not collaborative across decision makers that occur, and who may have individual objectives and tradeoffs, across spatial scales (Ernstson et al. 2008, Mills et al. 2014). Instead, we consider the two scales over which the amphibian community may be considered and allow for differential weighting of these two spatially-referenced objectives. This effectively discretizes spatial discounting relative to the multiple governance scales in a decision, and we can thus separately estimate the value of direct, local impacts and indirect, regional impacts of management for each wetland for all relevant decision makers.

We present a simplified approach to multi-scaled prioritization, and there are a number of developments and complexities that could be incorporated in future research. First, we assumed the region cares about the improvement in the amphibian community within all parks equally, but that may vary (e.g., the region may want to target areas where declines are the highest) and could be incorporated in the decision-making approach via differential values for the spatial weights. Second, we assumed that the cost of managing each wetland is the same, but that may vary, and decision makers may choose to incorporate cost in the value function. We also assumed that management is immediate and durable, however, both a delay in reaching the maximum species richness as well as the uncertainty and variation in the efficacy of management could be incorporated (e.g., Tallis et al. In Review). Lastly, we keep the metric to be maximized at the same scale (wetland-specific richness) and allow the weights to vary across and within scales, but the metric may vary by scale as well (e.g., the number of species in the region vs. the number of species in a park).

Overall, this approach can help spatially prioritize management action by discretizing objective weights (*how each decision maker cares about a conservation goal*) and spatial discounting parameters (*how each decision maker cares about individual vs collaborative goals*). Recognizing that conservation is collaborative, such an approach allows for the incorporation of decision makers operating at different scales, and having access to different resources, in a landscape conservation problem. Space and spatial scale matters—as population and community declines, impacts of management, and management objectives may vary across a landscape.

Table 3.1: Park-level mean effects on occupancy (on the normal scale) of trend and the semi-permanent wetland hydroperiod classification, summarized by the mean of the posterior distribution (and 95% Credible Intervals). Parks include: Catoctin Mountain Park (CATO), Chesapeake & Ohio Canal National Historical Park (CHOH), George Washington Memorial Parkway (GWMP), Harpers Ferry National Historical Park (HAFE), Manassas National Battlefield Park (MANA), Monocacy National Battlefield (MONO), National Capital Parks – East (NACE), Prince William Forest Park (PRWI), and Rock Creek Park (ROCR).

Park	Trend Effect	Semi-permanent Effect
CATO	-0.60 (-1.36 – 0.22)	0.96 (0.15 – 1.95)
CHOH	0.01 (-0.27 – 0.26)	0.46 (-0.08 – 0.97)
GWMP	-1.32 (-2.24 – -0.55)	0.64 (-0.03 – 1.31)
HAFE	-1.05 (-2.58 – 0.06)	0.62 (-0.39 – 1.65)
MANA	-0.63 (-1.13 – -0.16)	1.02 (0.38 – 1.70)
MONO	-1.09 (-1.87 – -0.36)	0.68 (-0.53 – 1.94)
NACE	-0.62 (-1.53 – 0.40)	0.40 (-0.59 – 1.19)
PRWI	-0.95 (-1.73 – -0.33)	0.58 (-0.04 – 1.19)
ROCR	-0.67 (-1.21 – -0.10)	0.67 (-0.60 – 1.86)

Table 3.2: Ranking of wetlands by impact, I, to species richness at each wetland (for 2021), including the species richness with (N_{Action}) and without management intervention (N_{BAU}) as well as the park in which each wetland is located. Parks include: Catoctin Mountain Park (CATO), Chesapeake & Ohio Canal National Historical Park (CHOH), George Washington Memorial Parkway (GWMP), Harpers Ferry National Historical Park (HAFE), Manassas National Battlefield Park (MANA), Monocacy National Battlefield (MONO), National Capital Parks – East (NACE), Prince William Forest Park (PRWI), and Rock Creek Park (ROCR).

Rank	N_{BAU}	N_{Action}	I	Park
1	2.51 (1.43)	5.25 (1.65)	2.74 (2.05)	MANA
2	2.76 (1.43)	5.45 (1.67)	2.69 (2.06)	MANA
3	2.36 (1.33)	5.04 (1.62)	2.68 (2.00)	MANA
4	2.24 (1.32)	4.91 (1.57)	2.67 (1.99)	MANA
5	2.10 (1.29)	4.75 (1.58)	2.66 (1.95)	MANA
…	…	…	…	…
71	1.58 (1.16)	2.68 (1.38)	1.10 (1.72)	PRWI
72	1.40 (1.07)	2.49 (1.52)	1.09 (1.75)	ROCR
73	1.31 (1.04)	2.40 (1.52)	1.08 (1.74)	ROCR
74	1.31 (1.08)	2.37 (1.33)	1.06 (1.64)	PRWI
75	2.63 (1.36)	3.62 (1.44)	1.00 (1.98)	CHOH
…	…	…	…	…
146	0.60 (0.76)	1.17 (1.03)	0.57 (1.26)	GWMP
147	1.07 (0.97)	1.64 (1.16)	0.57 (1.33)	NACE
148	0.59 (0.74)	1.16 (1.01)	0.57 (1.21)	GWMP

Table 3.2 (cont'd)

149	0.35 (0.57)	0.91 (0.99)	0.56 (1.16)	MONO
150	0.55 (0.74)	1.10 (1.00)	0.56 (1.20)	GWMP
…	…	…	…	…

Figure 3.1: Estimated annual mean wetland-specific species richness by park (black points) with 50% Credible Intervals (dark gray area) and 95% Credible Intervals (light gray area) from 2015-2020. Predicted annual mean wetland-specific species richness under the business as usual scenario by park (red points) with 50% Credible Intervals (dark red area) and 95% Credible Intervals (light red area) from 2021-2026, and under the management intervention (if every temporary wetland was manipulated to semi-permanent) scenario by park (blue points) with 50% Credible Intervals (dark blue area) and 95% Credible Intervals (light blue area) from 2021-2026. Parks include: Catoctin Mountain Park (CATO), Chesapeake & Ohio Canal National Historical Park (CHOH), George Washington Memorial Parkway (GWMP), Harpers Ferry National Historical Park (HAFE), Manassas National Battlefield Park (MANA), Monocacy National Battlefield (MONO), National Capital Parks – East (NACE), Prince William Forest Park (PRWI), and Rock Creek Park (ROCR).

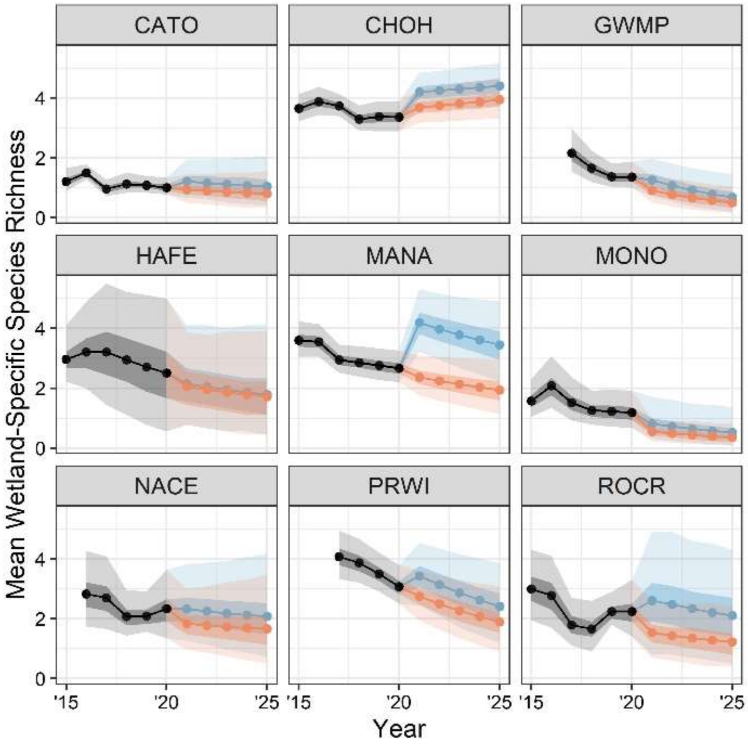


Figure 3.2: The net increase to mean wetland-specific richness by the percentage of temporary wetlands that are managed for the region (NCRN) and for each park. Parks include: Catoctin Mountain Park (CATO), Chesapeake & Ohio Canal National Historical Park (CHOH), George Washington Memorial Parkway (GWMP), Harpers Ferry National Historical Park (HAFE), Manassas National Battlefield Park (MANA), Monocacy National Battlefield (MONO), National Capital Parks – East (NACE), Prince William Forest Park (PRWI), and Rock Creek Park (ROCR).

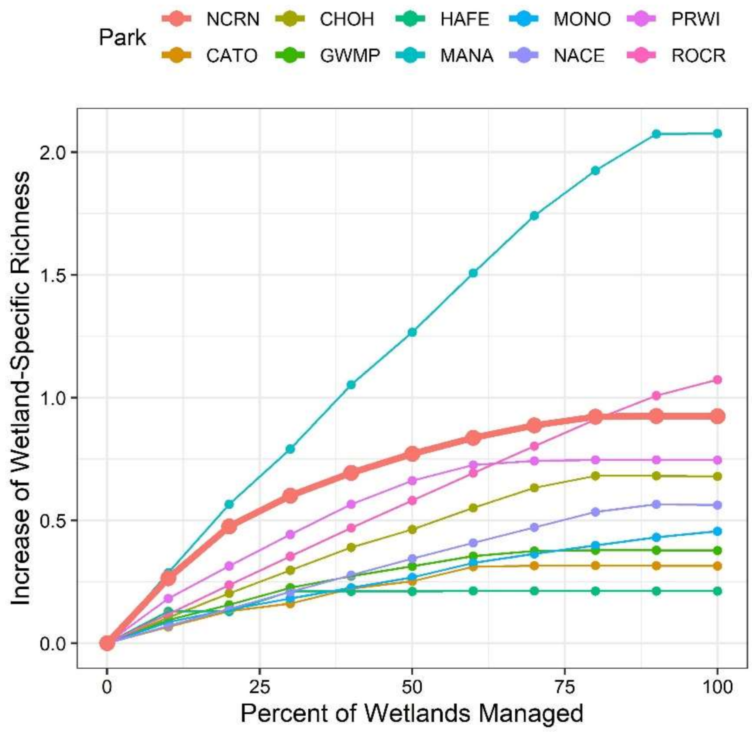


Figure 3.3: The mean impact of management, I, to wetland-specific species richness of the top quarter of wetlands across the NCRN ranked by different values of regional objective weights (w_{region}) as well as (a-b) local spatial discounting parameters (s_{unit}) and (c-d) objective weights (w_{unit}). We compare these values under four different hypothetical scenarios to visualize the variability among parks within each parameter: (a) s_{unit} and w_{region} vary from 0 to 1 (in increments of 0.1) but w_{unit} for each park is inversely proportional the amount of wetland habitat in the park; (b) s_{unit} and w_{region} vary from 0 to 1 (in increments of 0.1) but w_{unit} for each park is proportional to the amount of wetland habitat in the park; (c) w_{unit} and w_{region} vary from 0 to 1 (in increments of 0.1) but s_{unit} for each park is proportional to the amount of wetland habitat in the park; and (d) w_{unit} and w_{region} vary from 0 to 1 (in increments of 0.1) but s_{unit} for each park is proportional to the amount of wetland habitat in the park. w_{unit} reflects how local decision makers value increasing amphibian wetland richness at their unit, and w_{region} reflects how regional decision makers value the same objective across their regional jurisdiction. s_{unit} reflects how local decision makers value these goals at their local level relative to the broader region, and s_{region} reflects the importance of these goals elsewhere in the region (both parameters sum to 1).

Figure 3.3 (cont'd)

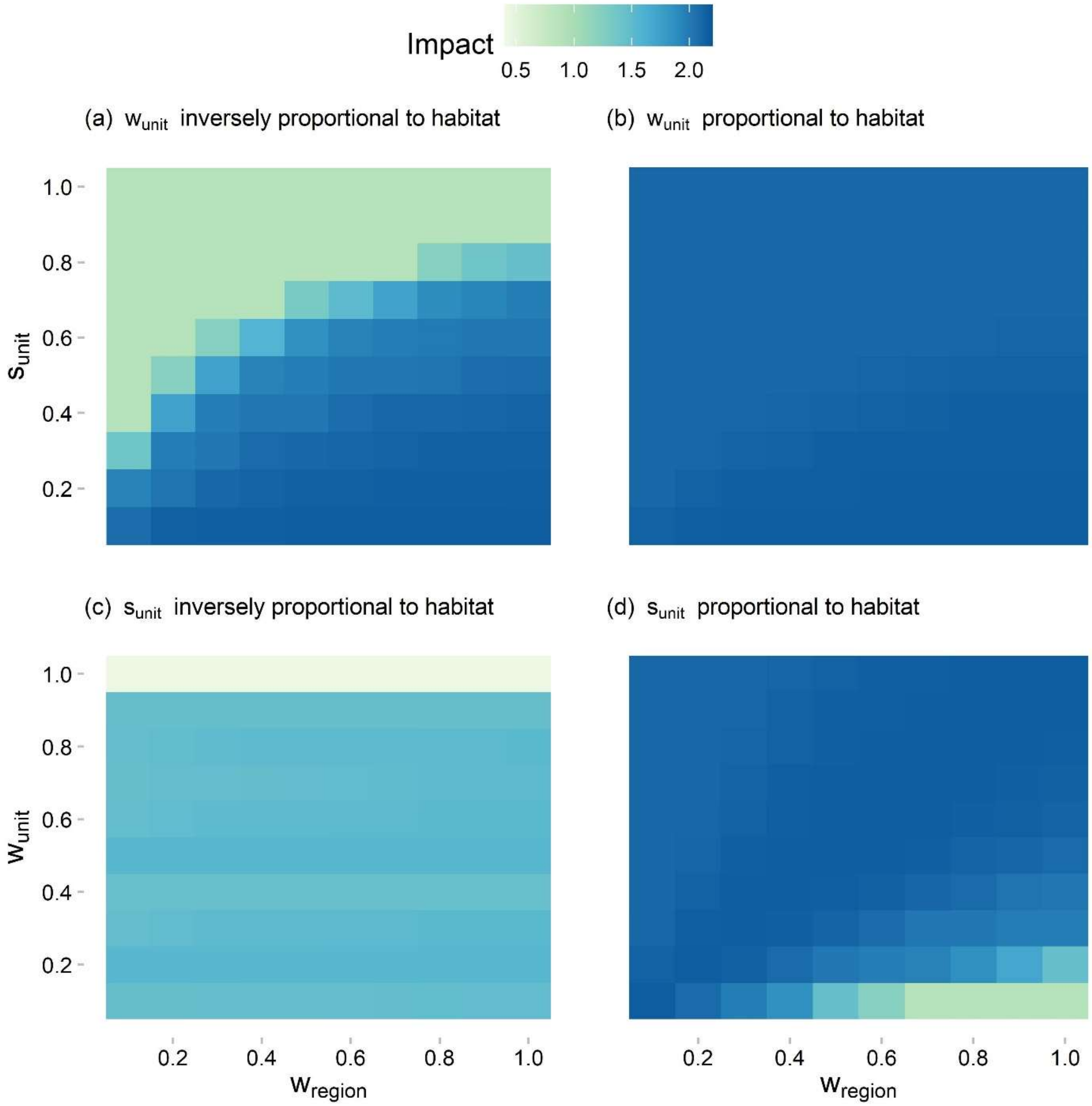
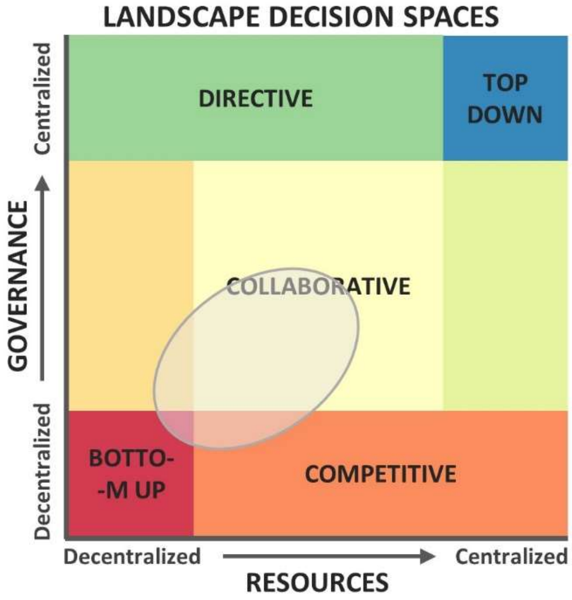


Figure 3.4: The different landscape decision spaces relative to the centralization of decision making authority ('governance') and management resources, using the approximate location of our case study (NCRN) in this space as an example (oval).



CHAPTER 4: MOVING FROM DECISION TO ACTION IN CONSERVATION SCIENCE

Abstract

Biodiversity loss is a major threat to the integrity of ecosystems and is projected to worsen, yet the path to successful conservation remains elusive. Decision support frameworks (DSFs) are increasingly applied by resource managers to navigate the complexity, uncertainty, and differing socio-ecological objectives inherent to conservation problems. Most published conservation research that uses DSFs focuses on analytical stages (e.g., identifying an optimal decision), making it difficult to assess and learn from previous examples in a conservation practice context. Here, we (1) evaluate the relationship between the application of decision science and the resulting conservation outcomes, and (2) identify and address existing barriers to the application of DSFs to conservation practice. To do this, we develop a framework for evaluating conservation initiatives using decision science that emphasizes setting attainable goals, building momentum, and obtaining partner buy-in. We apply this framework to a systematic review of amphibian conservation decision support projects, including a follow-up survey of the pertinent conservation practitioners, stakeholders, and scientists. We found that all projects identified optimal solutions to reach stated objectives, but positive conservation outcomes were limited when implementation challenges arose. Further, we identified multiple barriers (e.g., dynamic and hierarchical leadership, scale complexity, limited resource availability) that can inhibit the progression from decision identification to action implementation (i.e., 'decision-implementation gap'), and to successful conservation outcomes. Based on these results, we provide potential actionable steps and avenues for future development

of DSFs to facilitate the transition from decision to action and the realization of conservation successes.

Material from: Wright, A. D., Bernard, R. F., Mosher, B. A., O'Donnell, K. M., Braunagel, T., DiRenzo, G. V., Fleming, J., Shafer, C., Brand, A. B., Zipkin, E. F., & Grant, E. H. C. (2020). Moving from decision to action in conservation science. *Biological Conservation*, *249*, 108698.

For full text of this work, please go to: https://doi.org/10.1016/j.biocon.2020.108698

APPENDICES

APPENDIX A: Data simulation and analysis code for simulations.

Data simulation and analysis code for the stratified random design at the 10% effort level. The full data simulation and analysis code is available on Zenodo (10.5281/zenodo.4577521). The symbols corresponding to the slope parameters for each effect term do not match directly as represented in the manuscript. In the manuscript, a1 corresponds to the time effect but is denoted by a2 in the code. Likewise, a2 in the manuscript corresponds to the site effect but is denoted by a1 in the code.

```
#########
## Part - General Code Description
#########

## Author: A.D. Wright
## Project: NCRN Amphibians - Monitoring Optimization
## Code: Data simulation and analysis for the Random Stratified case study

#rm(list = ls())
#options(max.print = 1000)

## TABLE OF CONTENTS
  ## Packages, working directory, and data
  ## Global parameters for simulation
  ## General f() to simulate data
  ## Generating data for each scenario

#########
## Part - Packages, working directory, and data
#########

##
#### Install Packages
##

#tidyverse
if(!require(tidyverse)) {install.packages('tidyverse');require(tidyverse)}
#jagsUI
if(!require(jagsUI)) {install.packages('jagsUI');require(jagsUI)}


#########
```

```
## Part - Global parameters for simulation
#########

set.seed(25)

##
#### Sampling dimensions
##

#Years
Y <- 10
#Sampling Occassions per Year
K <- 6
Kmed <- 4
Klow <- 2

#Units
R <- 10
#Sites per unit
JMax <- 100
JMin <- 10
Jr <- as.integer(runif(n = R, min = JMin, max = JMax))

#Species Total (will vary by park)
I <- 25
M <- 25

#Datasets per scenario
#5 sampling scenarios:
scenarios <- c('stratified','indicator','rotating','split','weighted')
#5 sampling efforts: #(10%, 20%, 30%, 40%, 50%)
effort <- c(0.1, 0.2, 0.3, 0.4, 0.5)


##
#### Global, regional, and species parameters
##

#Global
#Unit Occupancy
mean.c0 <- 0.4
sd.c0 <- 0.25
#Site Occupancy
#Intercept
mean.a0.global <- 0.3
sd.a0.global <- 0.5
```

```
sd.a0 <- 0.5
#Site effect
mu.a1.global <- 0.8
sd.a1.global <- 0.5
sd.a1 <- 0.5
#Year effect
mu.a2.global <- -0.4
sd.a2.global <- 0.5
sd.a2 <- 0.5
#Autologistic effect
mu.a3.global <- 0.4
sd.a3.global <- 0.5
sd.a3 <- 0.5
#Detection
mean.b0.global <- 0.3
sd.b0.global <- 0.5
sd.b0 <- 0.5

##
#### Generate covariate data
##

Site_effect_a1 <- array(rnorm(JMax*R, 0, 1), dim = c(100,10))
Year <- 1:10
Year_effect_a2 <- (Year - mean(Year))/sd(Year)


#########
## Part - f()'s
#########


##
#### Simulation f() - A blend of Sutherland et al. 2016 S2 & simDCM
##

#Basic Function
sim_community <- function(R. = R, # of spatial units
                          I. = I, # of species
                          M. = M, # of augmented species
                          Y. = Y, # of years
                          K. = K, # of sampling occassions per year
                          JMax = max(Jr), # sites max per unit
                          Jr. = Jr, # of sites per spatial unit
                          mean.c0. = mean.c0, sd.c0. = sd.c0,  #unit occupancy
```

```
                    mean.a0.global. = mean.a0.global, sd.a0.global. = sd.a0.global, sd.a0. = sd.a0,
#site occupancy
                    mu.a1.global. = mu.a1.global, sd.a1.global. = sd.a1.global, sd.a1. = sd.a1,
#site effect on occupancy
                    mu.a2.global. = mu.a2.global, sd.a2.global. = sd.a2.global, sd.a2. = sd.a2,
#year effect on occupancy
                    mu.a3.global. = mu.a3.global, sd.a3.global. = sd.a3.global, sd.a3. = sd.a3,
#auto effect on occupancy
                    mean.b0.global. = mean.b0.global, sd.b0.global. = sd.b0.global, sd.bo. = sd.b0,
#detection
                    Site_effect_a1. = Site_effect_a1, Year_effect_a2. = Year_effect_a2
#covariates
){

  #Create empty objects for loops
  #Region (and species - in 2nd loop)
  mu.a0 <- mu.a1 <- mu.a2 <- mu.a3 <- mu.b0 <- omega <- N_unit <- array(NA, dim = R)
  a0 <- a1 <- a2 <- a3 <- b0 <- array(NA, dim = c(I+M,R))
  W_mat <- array(NA, c(I+M,R))
  Z_mat <- logit_psi <- array(NA, c(JMax, Y, I+M, R))
  X_mat <- array(NA, c(JMax, K, Y, I+M, R))

  #Generate park and species parameters
  for(r in 1:R){
    omega[r] <- plogis(rnorm(1,qlogis(mean.c0),sd.c0))
    #Occupancy
    mu.a0[r] <- rnorm(1, mean = qlogis(mean.a0.global), sd = sd.a0.global)
    mu.a1[r] <- rnorm(1, mean = mu.a1.global, sd = sd.a1.global)
    mu.a2[r] <- rnorm(1, mean = mu.a2.global, sd = sd.a2.global)
    mu.a3[r] <- rnorm(1, mean = mu.a3.global, sd = sd.a3.global)
    #Detection
    mu.b0[r] <- rnorm(1, mean = qlogis(mean.b0.global), sd = sd.b0.global)
    for(i in 1:(I+M)){
      W_mat[i,r] <- rbinom(1, 1, omega[r])
      #Species
      #Occupancy
      a0[i,r] <- rnorm(1, mean = mu.a0[r], sd = sd.a0)
      a1[i,r] <- rnorm(1, mean = mu.a1[r], sd = sd.a1)
      a2[i,r] <- rnorm(1, mean = mu.a2[r], sd = sd.a2)
      a3[i,r] <- rnorm(1, mean = mu.a3[r], sd = sd.a3)
      #Detection
      b0[i,r] <- rnorm(1, mean = mu.b0[r], sd = sd.b0)
    }
    N_unit[r] <- sum(W_mat[,r])
  }
```

```
  #Generate data
  for(r in 1:R){
    for(i in 1:(I+M)){
      for(j in 1:Jr[r]) {
        logit_psi[j,1,i,r] <- a0[i,r] + a1[i,r]*Site_effect_a1[j,r] + a2[i,r]*Year_effect_a2[1]
        Z_mat[j,1,i,r] <- rbinom(1, 1, plogis(logit_psi[j,1,i,r])*W_mat[i,r])
        for(y in 2:Y){
          logit_psi[j,y,i,r] <- a0[i,r] + a1[i,r]*Site_effect_a1[j,r] + a2[i,r]*Year_effect_a2[y] +
a3[i,r]*Z_mat[j,y-1,i,r]
          Z_mat[j,y,i,r] <- rbinom(1, 1, plogis(logit_psi[j,y,i,r])*W_mat[i,r])
        } #y
        for(y in 1:Y){
          for(k in 1:K){
            X_mat[j,k,y,i,r] <- rbinom(1, 1, Z_mat[j,y,i,r]*plogis(b0[i,r]))
          } #k
        } #y
      } #j
    } #i
  } #r

  return(list(X_mat = X_mat, logit_psi = logit_psi, Z_mat = Z_mat,
#the simulated data
              R = R, I = I, M = M, Y = Y, K = K, JMax = JMax, Jr = Jr,
#the dimensions used to simulate the data
              Site_effect_a1 = Site_effect_a1, Year_effect_a2 = Year_effect_a2,
#the covariates used to simulate the data
              mean.c0 = mean.c0, sd.c0 = sd.c0, omega = omega, W_mat = W_mat, N_unit = N_unit,
#the parameters used to simulate data - unit occupancy
              mean.a0.global = mean.a0.global, sd.a0.global = sd.a0.global, sd.a0 = sd.a0, mu.a0 =
mu.a0, a0 = a0,     #the parameters used to simulate data - site occupancy (intercept)
              mu.a1.global = mu.a1.global, sd.a1.global = sd.a1.global, sd.a1 = sd.a1, mu.a1 = mu.a1,
a1 = a1,        #the parameters used to simulate data - site occupancy (slope - site)
              mu.a2.global = mu.a2.global, sd.a2.global = sd.a2.global, sd.a2 = sd.a2, mu.a2 = mu.a2,
a2 = a2,        #the parameters used to simulate data - site occupancy (slope - year)
              mu.a3.global = mu.a3.global, sd.a3.global = sd.a3.global, sd.a3 = sd.a3, mu.a3 = mu.a3,
a3 = a3,        #the parameters used to simulate data - site occupancy (slope - auto)
              mean.b0.global = mean.b0.global, sd.b0.global = sd.b0.global, sd.b0 = sd.b0, mu.b0 =
mu.b0, b0 = b0      #the parameters used to simulate data - detection (intercept)
  ))

} #f() - sim_community



##
#### Base function to create tables of results for plotting purposes
```

```
##

org_results <- function(jagsOut, td){

  nPark <- td$R
  nSpp <- dim(td$W_mat)[1]*dim(td$W_mat)[2]

  #Global
  simTab_g <- data.frame(mean.c0 = NA,
                         sd.c0 = NA,
                         mu.a0.global = NA,
                         sd.a0.global = NA,
                         sd.a0 = NA,
                         mu.b0.global = NA,
                         sd.b0.global = NA,
                         sd.b0 = NA,
                         mu.a1.global = NA,
                         sd.a1.global = NA,
                         sd.a1 = NA,
                         mu.a2.global = NA,
                         sd.a2.global = NA,
                         sd.a2 = NA,
                         mu.a3.global = NA,
                         sd.a3.global = NA,
                         sd.a3 = NA
                        )

  simTab_g$mean.c0 <- jagsOut$mean$mean.c0 - td$mean.c0
  simTab_g$sd.c0 <- jagsOut$mean$sd.c0 - td$sd.c0
  simTab_g$mu.a0.global <- jagsOut$mean$mu.a0.global - mean(td$mu.a0)
  simTab_g$sd.a0.global <- jagsOut$mean$sd.a0.global - td$sd.a0.global
  simTab_g$sd.a0 <- jagsOut$mean$sd.a0 - td$sd.a0
  simTab_g$mu.a1.global <- jagsOut$mean$mu.a1.global - mean(td$mu.a1)
  simTab_g$sd.a1.global <- jagsOut$mean$sd.a1.global - td$sd.a1.global
  simTab_g$sd.a1 <- jagsOut$mean$sd.a1 - td$sd.a1
  simTab_g$mu.a2.global <- jagsOut$mean$mu.a2.global - mean(td$mu.a2)
  simTab_g$sd.a2.global <- jagsOut$mean$sd.a2.global - td$sd.a2.global
  simTab_g$sd.a2 <- jagsOut$mean$sd.a2 - td$sd.a2
  simTab_g$mu.a3.global <- jagsOut$mean$mu.a3.global - mean(td$mu.a3)
  simTab_g$sd.a3.global <- jagsOut$mean$sd.a3.global - td$sd.a3.global
  simTab_g$sd.a3 <- jagsOut$mean$sd.a3 - td$sd.a3
  simTab_g$mu.b0.global <- jagsOut$mean$mu.b0.global - mean(td$mu.b0)
  simTab_g$sd.b0.global <- jagsOut$mean$sd.b0.global - td$sd.b0.global
  simTab_g$sd.b0 <- jagsOut$mean$sd.b0 - td$sd.b0

  #Park
```

```
  simTab_p <- data.frame(mu.a0 = rep(NA,nPark),
                          mu.b0 = rep(NA,nPark),
                          mu.a1 = rep(NA,nPark),
                          mu.a2 = rep(NA,nPark),
                          mu.a3 = rep(NA,nPark)
                         )

  simTab_p$mu.a0[1:nPark] <- (jagsOut$mean$mu.a0 - apply(td$a0,2,mean))
  simTab_p$mu.a1[1:nPark] <- (jagsOut$mean$mu.a1 - apply(td$a1,2,mean))
  simTab_p$mu.a2[1:nPark] <- (jagsOut$mean$mu.a2 - apply(td$a2,2,mean))
  simTab_p$mu.a3[1:nPark] <- (jagsOut$mean$mu.a3 - apply(td$a3,2,mean))
  simTab_p$mu.b0[1:nPark] <- (jagsOut$mean$mu.b0 - apply(td$b0,2,mean))

  #Species
  simTab_s <- data.frame(a0 = rep(NA,nSpp),
                          b0 = rep(NA,nSpp),
                          a1 = rep(NA,nSpp),
                          a2 = rep(NA,nSpp),
                          a3 = rep(NA,nSpp)
  )

    simTab_s$a0[1:nSpp] <- as.vector(jagsOut$mean$a0*na_if(td$W_mat, 0)) -
(td$a0*na_if(td$W_mat, 0))
    simTab_s$b0[1:nSpp] <- as.vector(jagsOut$mean$b0*na_if(td$W_mat, 0)) -
(td$b0*na_if(td$W_mat, 0))
    simTab_s$a1[1:nSpp] <- as.vector(jagsOut$mean$a1*na_if(td$W_mat, 0)) -
(td$a1*na_if(td$W_mat, 0))
    simTab_s$a2[1:nSpp] <- as.vector(jagsOut$mean$a2*na_if(td$W_mat, 0)) -
(td$a2*na_if(td$W_mat, 0))
    simTab_s$a3[1:nSpp] <- as.vector(jagsOut$mean$a3*na_if(td$W_mat, 0)) -
(td$a3*na_if(td$W_mat, 0))


  #Put results all together
  x <- list(global = simTab_g, park = simTab_p, species = simTab_s)
  return(x)

}


#########
## Part - Loop to run multiple simulations
#########


## Looping Variables
```

```
start <- 1
end <- 10 #Run this script 65 times in HPCC for a total of 650 sims: for i in {1..65}; do sbatch
amphibianRS.sb; done
results <- Jr_temp <- maxJr_temp <- K_temp <- list()
converge <- vector()

##Loop
for(i in start:end){

  #Remove seed so simulations in parallel are all different
  set.seed(NULL)

  #Simulate a data set
  td <- sim_community()

  ## Simulation specific variables
  strategy <- "randomStrat"
  effort <- 0.5
  Jr_temp[[i]] <- round(td$Jr*effort)
  maxJr_temp[[i]] <- max(Jr_temp[[i]])
  K_temp[[i]] <- 4

  #Need to rewrite Z_mat and W_mat based on effort for initial values
  for(r in 1:td$R){
    for(m in 1:(td$I+td$M)){
      for(j in (Jr_temp[[i]][r]+1):td$JMax) {
        for(y in 1:td$Y){
            td$Z_mat[j,y,m,r] <- NA
          for(k in 1:6){
            td$X_mat[j,k,y,m,r] <- NA
          } #k
        } #y
      } #j
    } #i
  } #r

  td$X_mat <- td$X_mat[1:maxJr_temp[[i]],1:K,1:10,1:50,1:10]
  td$Z_mat <- td$Z_mat[1:maxJr_temp[[i]],1:10,1:50,1:10]

  # Organize data for jags
  jagsDat <- list(X = td$X_mat, #Detection data
                R = td$R, I = td$I, M = td$M, Y = td$Y, K = K_temp[[i]], Jr = Jr_temp[[i]],
#Looping variables
                Site_effect_a1 = td$Site_effect_a1, Year_effect_a2 = td$Year_effect_a2 #Covariates
                )
```

```
  # Compile initital values for jags
  jagsIni <- function(){
    list(Z=td$Z_mat, W=td$W_mat)
  }

  # Paramaters to monitor for jags
  jagsPar <- c('mean.c0', 'sd.c0',                                      #unit occupancy
               'mu.a0.global', 'sd.a0.global', 'sd.a0', 'mu.a0', 'a0',  #site occupancy (intercept)
               'mu.a1.global', 'sd.a1.global', 'sd.a1', 'mu.a1', 'a1',  #site occupancy (slope)
               'mu.a2.global', 'sd.a2.global', 'sd.a2', 'mu.a2', 'a2',  #site occupancy (slope)
               'mu.a3.global', 'sd.a3.global', 'sd.a3', 'mu.a3', 'a3',  #site occupancy (slope)
               'mu.b0.global', 'sd.b0.global', 'sd.b0', 'mu.b0', 'b0'   #detection (intercept)
  )


  #Run jags()
  jagsFit <- autojags(data = jagsDat,
                      inits = jagsIni,
                      parameters.to.save = jagsPar,
                      model.file = "mrcm_jags.txt",
                      parallel=T,
                      n.chains=3,
                      n.adapt=1000,
                      iter.increment=10000,
                      max.iter=50000,
                      n.burnin=5000,
                      n.thin=10,
                      Rhat.limit = 1.11
                     )

  # Append this run to one full results object
  results[[i]] <- org_results(jagsOut = jagsFit, td = td)
  converge[i] <- max(unlist(jagsFit$Rhat))

}# END OF LOOP


##Save results file
date <- gsub(pattern = c(":| "), replacement = "-", x = as.character(Sys.time()))

file_str <- paste("jagsFit_","Simul_", effort*100, strategy,"_",date,".R",sep="")
#Save
save(results, converge, file=file_str)
```

APPENDIX B: Monitoring design sampling schemes for simulations.

Table B.1: The percentage of sites sampled at each unit across all years in the stratified random and weighted effort designs at 10% effort. In the stratified random design, each site sampled has 4 replicate visits per year. In the weighted effort design, sites at units 1-5 received 6 replicate visits per year, and sites at units 6-10 received 2 replicate visits per year.

Unit / # of Total Sites	Year									
	1	2	3	4	5	6	7	8	9	10
1 (16)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
2 (21)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
3 (47)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
4 (72)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
5 (98)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
6 (23)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
7 (40)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
8 (66)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
9 (35)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
10 (90)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%

Table B.2: The percent of sites sampled at each unit across all years in the indicator unit design at 10% effort. Each site sampled has 4 replicate visits per year.

Unit / # of Total Sites	Year									
	1	2	3	4	5	6	7	8	9	10
1 (16)	20%	20%	20%	20%	20%	20%	20%	20%	20%	20%
2 (21)	20%	20%	20%	20%	20%	20%	20%	20%	20%	20%
3 (47)	20%	20%	20%	20%	20%	20%	20%	20%	20%	20%
4 (72)	20%	20%	20%	20%	20%	20%	20%	20%	20%	20%
5 (98)	20%	20%	20%	20%	20%	20%	20%	20%	20%	20%
6 (23)										
7 (40)										
8 (66)										
9 (35)										
10 (90)										

Table B.3: The percent of sites sampled at each unit across all years in the rotating panel design at 10% effort. Each site sampled has 4 replicate visits per year.

Unit / # of Total Sites	Year									
	1	2	3	4	5	6	7	8	9	10
1 (16)	20%	20%			20%	20%			20%	20%
2 (21)	20%	20%			20%	20%			20%	20%
3 (47)	20%	20%			20%	20%			20%	20%
4 (72)	20%	20%			20%	20%			20%	20%
5 (98)	20%	20%			20%	20%			20%	20%
6 (23)			20%	20%			20%	20%		
7 (40)			20%	20%			20%	20%		
8 (66)			20%	20%			20%	20%		
9 (35)			20%	20%			20%	20%		
10 (90)			20%	20%			20%	20%		

Table B.4: The percent of sites sampled at each unit across all years in the split panel design at 10% effort. Each site sampled has 4 replicate visits per year.

Unit / # of Total Sites	Year									
	1	2	3	4	5	6	7	8	9	10
1 (16)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
2 (21)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
3 (47)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
4 (72)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
5 (98)	10%	10%	10%	10%	10%	10%	10%	10%	10%	10%
6 (23)	20%	20%			20%	20%			20%	20%
7 (40)	20%	20%			20%	20%			20%	20%
8 (66)	20%	20%			20%	20%			20%	20%
9 (35)			20%	20%			20%	20%		
10 (90)			20%	20%			20%	20%		

APPENDIX C: Multi-region community occupancy model for simulations.

The full data simulation and analysis code is available on Zenodo (10.5281/zenodo.4577521). The symbols corresponding to the slope parameters for each effect term do not match directly as represented in the manuscript. In the manuscript, a1 corresponds to the time effect but is denoted by a2 in the code. Likewise, a2 in the manuscript corresponds to the site effect but is denoted by a1 in the code.

JAGS code:

```
model{

#########
## Part - General Model Description
#########

# Author: A.D. Wright
# Description: This dynamic (autologistic) occupancy model analyzes simulated data. It treats species &
park hierarchically - an "MRCM" model (Sutherland et al 2016)

# Subscripts:
  # i = Species; I = nSpecies; M = nZeroes
  # j = Site; Jr = nSites per Unit; Jsamp = nSites per Unit that were sampled
  # r = Unit; R = nUnit
  # k = Visit; K = nVisits
  # y = Year; Y = nYears

# Effects
  # Omega:     Intercept
  # Occupancy: Intercept + Site_effect + Year_effect + Autologistic_effect
  # Detection: Intercept

#########
## Part - Priors
#########

##
#### Global-level priors
##

#Data Augmentation
  #Intercept
mean.c0 ~ dunif(0,1)
mu.c0 <- log(mean.c0/(1-mean.c0))
sd.c0 ~ dunif(0,10)
tau.c0 <- pow(sd.c0, -2)

#Occupancy
  #Intercepts
```

```
mu.a0.global ~ dnorm(0, 0.37)
sd.a0.global ~ dunif(0,10)
sd.a0 ~ dunif(0,10)
tau.a0.global <- pow(sd.a0.global, -2)
tau.a0 <- pow(sd.a0, -2)
  #Slopes
    #Site Effect
mu.a1.global ~ dnorm(0,0.1)
sd.a1.global ~ dunif(0,10)
sd.a1 ~ dunif(0,10)
tau.a1.global <- pow(sd.a1.global, -2)
tau.a1 <- pow(sd.a1, -2)
    #Time effect
mu.a2.global ~ dnorm(0,0.1)
sd.a2.global ~ dunif(0,10)
sd.a2 ~ dunif(0,10)
tau.a2.global <- pow(sd.a2.global, -2)
tau.a2 <- pow(sd.a2, -2)
    #Autologistic effect
mu.a3.global ~ dnorm(0,0.1)
sd.a3.global ~ dunif(0,10)
sd.a3 ~ dunif(0,10)
tau.a3.global <- pow(sd.a3.global, -2)
tau.a3 <- pow(sd.a3, -2)

#Detection
  #Intercepts
mu.b0.global ~ dunif(0,0.37)
sd.b0.global ~ dunif(0,10)
sd.b0 ~ dunif(0,10)
tau.b0.global <- pow(sd.b0.global, -2)
tau.b0 <- pow(sd.b0, -2)

##
#### Region-level priors
##

for (r in 1:R) {

  #Data Augmentation
  l.omega[r] ~ dnorm(mu.c0, tau.c0)
  logit(omega[r]) <- l.omega[r]
  #Occupancy
    #Intercept
  mu.a0[r] ~ dnorm(mu.a0.global, tau.a0.global)
    #Slopes
  mu.a1[r] ~ dnorm(mu.a1.global, tau.a1.global)
  mu.a2[r] ~ dnorm(mu.a2.global, tau.a2.global)
  mu.a3[r] ~ dnorm(mu.a3.global, tau.a3.global)

  #Detection
    #Intercept
  mu.b0[r] ~ dnorm(mu.b0.global, tau.b0.global)

##
#### Species-level priors
```

```
##

 for (i in 1:(I+M)) {

   #Data Augmentation
   W[i,r] ~ dbern(omega[r])

   #Occupancy
     #Intercepts
   a0[i,r] ~ dnorm(mu.a0[r],tau.a0)
     #Slopes
   a1[i,r] ~ dnorm(mu.a1[r],tau.a1)
   a2[i,r] ~ dnorm(mu.a2[r],tau.a2)
   a3[i,r] ~ dnorm(mu.a3[r],tau.a3)

   #Detection
     #Intercepts
   b0[i,r] ~ dnorm(mu.b0[r],tau.b0)


#########
## Part - Likelihood
#########

##
#### Estimating Occupancy (Z-Array)
##

   for (j in 1:Jr[r]) {

       logit(psi[j,1,i,r]) <- a0[i,r] + a1[i,r]*Site_effect_a1[j,r] + a2[i,r]*Year_effect_a2[1]
       Z[j,1,i,r] ~ dbern(psi[j,1,i,r]*W[i,r])

     for (y in 2:Y) {

         logit(psi[j,y,i,r]) <- a0[i,r] + a1[i,r]*Site_effect_a1[j,r] + a2[i,r]*Year_effect_a2[y] + a3[i,r]*Z[j,y-1,i,r]
         Z[j,y,i,r] ~ dbern(psi[j,y,i,r]*W[i,r])

     } #y

##
#### Estimating Detection (Data-Array)
##

     for (y in 1:Y) {

       for (k in 1:K) {

         logit(p[j,k,y,i,r]) <- b0[i,r]
         X[j,k,y,i,r] ~ dbern(p[j,k,y,i,r]*Z[j,y,i,r])

       } #k
     } #y
   } #j
 } #i
} #r
```

```
##
#### Imputation model (this is needed for the IU design)
##

for (r in 1:R) {

  for (j in 1:Jr[r]) {

    Site_effect_a1[j,r] ~ dnorm(0, 1)

  } #j
} #r


#########
## Part -  END
#########

} #model
```

APPENDIX D: JAGS model for analysis of 2005-2020 data.

We conducted our analyses within a Bayesian program using JAGS (Plummer 2003), R (R Core Team 2016), and the 'jagsUI' package (Kellner 2016). All continuous covariates were standardized to have a mean of zero and a standard deviation of one, and missing covariate data were estimated using an imputation approach (Kéry and Royle 2015). We assessed structural parameters for convergence by visually monitoring the corresponding trace plots and assuring that the Gelman and Rubin diagnostic was less than 1.1 (Gelman and Rubin 1992; Gelman and Shirley 2011; Kéry and Royle 2015).

JAGS code:

```
model{

#########
## Part - General Model Description
#########


# Author: A.D. Wright
# Description: This occupancy model analyzes 2005-2020 NCRN data (collected by NEARMI and NCR).
It treats species & park hierarchically.
        #Uses components of Zipkin et al 2009 (based on Dorazio & Royle 2005, Dorazio et al 2006) and
Sutherland et al 2016.

# Subscripts:
  # i = Species; I = nSpecies; M = nZeroes
  # j = Site; J = nSites; minJ = Vector containing indices of first site in a region; maxJ = ....of last site in a
region
  # r = Region; R = nRegions
  # k = Visit; K = nReps (in years that site[j] is not sampled, K is set to 1 to generate missing data)
  # y = Year; Y = nYears; minY = Vector containg indices of first year of sampling for a site

# Effects
  # Omega:     Intercept
  # Occupancy: Hydroperiod (Intercept) + Maximum Wetland Area  + Connectivity + Conductivity + Trend
  # Detection: Intercept + Julian Date + (Julian Date)^2 + RE of Year (for variation among technicians)


#########
## Part - Priors
#########

##
#### Global-level priors
##
```

```
#Data Augmentation
  #Intercept
mu.omega ~ dnorm(0,0.37)
tau.omega ~ dgamma(0.1,0.1)

#Occupancy
  #Intercept (temporary wetlands)
logit(mean.a0.global) <- mu.a0.global
mu.a0.global ~ dnorm(0,0.37)
tau.a0.global ~ dgamma(0.1,0.1)
tau.a0 ~ dgamma(0.1,0.1)
  #Hydroperiod effects
mu.a1_S.global ~ dnorm(0,0.1)
tau.a1_S.global ~ dgamma(0.1,0.1)
tau.a1_S ~ dgamma(0.1,0.1)
mu.a1_P.global ~ dnorm(0,0.1)
tau.a1_P.global ~ dgamma(0.1,0.1)
tau.a1_P ~ dgamma(0.1,0.1)
  #Other effects
mu.a2.global ~ dnorm(0,0.1)                   #Defines mean of a2[i,r], slope of Area (psi) for each
species
tau.a2.global ~ dgamma(0.1,0.1)                 #Defines precision (1/sd^2) of mu.a2[r]
tau.a2 ~ dgamma(0.1,0.1)                      #Defines precision (1/sd^2) of a2[i,r]
mu.a3.global ~ dnorm(0,0.1)                   #Defines mean of a3[i,r], slope of Connectivity (psi) for
each species
tau.a3.global ~ dgamma(0.1,0.1)                 #Defines precision (1/sd^2) of mu.a3[r]
tau.a3 ~ dgamma(0.1,0.1)                      #Defines precision (1/sd^2) of a3[i,r]
mu.a4.global ~ dnorm(0,0.1)                   #Defines mean of a4[i,r], slope of Conductivity (psi) for
each species
tau.a4.global ~ dgamma(0.1,0.1)                 #Defines precision (1/sd^2) of mu.a4[r]
tau.a4 ~ dgamma(0.1,0.1)                      #Defines precision (1/sd^2) of a4[i,r]
mu.a5.global ~ dnorm(0,0.1)                   #Defines mean of a5[i,r], slope of Year (psi) for each
species
tau.a5.global ~ dgamma(0.1,0.1)                 #Defines precision (1/sd^2) of mu.a5[r]
tau.a5 ~ dgamma(0.1,0.1)                      #Defines precision (1/sd^2) of a5[i,r]

#Detection
  #Intercepts
mu.b0.global ~ dnorm(0,0.37)                   #Defines mean of b0[i,r], intercept (p) for each species
tau.b0.global ~ dgamma(0.1,0.1)                 #Defines precision (1/sd^2) of mu.b0[r]
tau.b0 ~ dgamma(0.1,0.1)                      #Defines precision (1/sd^2) of b0[i,r]
  #Slopes
mu.b1.global ~ dnorm(0,0.1)                   #Defines mean of b1[i,r], slope of JDay (p) for each
species
tau.b1.global ~ dgamma(0.1,0.1)                 #Defines precision (1/sd^2) of mu.b1[r]
tau.b1 ~ dgamma(0.1,0.1)                      #Defines precision (1/sd^2) of b1[i,r]
mu.b2.global ~ dnorm(0,0.1)                   #Defines mean of b2[i,r], slope of JDay^2 (p) for each
species
tau.b2.global ~ dgamma(0.1,0.1)                 #Defines precision (1/sd^2) of mu.b2[r]
tau.b2 ~ dgamma(0.1,0.1)                      #Defines precision (1/sd^2) of b2[i,r]
  #Random-effect of time
tau.b.time ~ dgamma(0.1,0.1)                   #Defines precision (1/sd^2) of eta[y], random effect of
annual field crew (p)
for (y in 1:Y){
  eta[y] ~ dnorm(0,tau.b.time)                #Defines random effect of annual field crew
} #y
```

```
##
#### Region-level priors
##

for (r in 1:R) {

  #Data Augmentation
  l.omega[r] ~ dnorm(mu.omega, tau.omega)
  logit(omega[r]) <- l.omega[r]

  #Occupancy
    #Intercept
  mu.a0[r] ~ dnorm(mu.a0.global, tau.a0.global)
    #Effects
  mu.a1_S[r] ~ dnorm(mu.a1_S.global,tau.a1_S.global)
  mu.a1_P[r] ~ dnorm(mu.a1_P.global,tau.a1_P.global)
  mu.a2[r] ~ dnorm(mu.a2.global, tau.a2.global)
  mu.a3[r] ~ dnorm(mu.a3.global, tau.a3.global)
  mu.a4[r] ~ dnorm(mu.a4.global, tau.a4.global)
  mu.a5[r] ~ dnorm(mu.a5.global, tau.a5.global)

  #Detection
    #Intercept
  mu.b0[r] ~ dnorm(mu.b0.global, tau.b0.global)
    #Slopes
  mu.b1[r] ~ dnorm(mu.b1.global, tau.b1.global)
  mu.b2[r] ~ dnorm(mu.b2.global, tau.b2.global)


##
#### Species-level priors
##

  for (i in 1:(I+M)) {

    #Data Augmentation
    W[i,r] ~ dbern(omega[r])

    #Occupancy
      #Intercepts
    a0[i,r] ~ dnorm(mu.a0[r],tau.a0)
      #Effects
    a1_S[i,r] ~ dnorm(mu.a1_S[r],tau.a1_S)
    a1_P[i,r] ~ dnorm(mu.a1_P[r],tau.a1_P)
    a2[i,r] ~ dnorm(mu.a2[r],tau.a2)
    a3[i,r] ~ dnorm(mu.a3[r],tau.a3)
    a4[i,r] ~ dnorm(mu.a4[r],tau.a4)
    a5[i,r] ~ dnorm(mu.a5[r],tau.a5)

    #Detection
      #Intercepts
    b0[i,r] ~ dnorm(mu.b0[r],tau.b0)
      #Slopes
    b1[i,r] ~ dnorm(mu.b1[r],tau.b1)
    b2[i,r] ~ dnorm(mu.b2[r],tau.b2)
```

```
#########
## Part - Likelihood
#########

##
#### Estimating Occupancy (Z-Array)
##

    for (j in minJ[r]:maxJ[r]) {
      for (y in minY[r]:Y) {

        logit(psi[j,y,i,r]) <- a0[i,r] + a1_S[i,r]*Hydro_state[j,2] + a1_P[i,r]*Hydro_state[j,3] +
a2[i,r]*Site_area[j,y] + a3[i,r]*Conn[j] + a4[i,r]*Cond[j,y] + a5[i,r]*Year[y]
        Z[j,y,i,r] ~ dbern(psi[j,y,i,r]*W[i,r])

      } #y

      zLast[j,i] <- Z[j,16,i,r]

##
#### Estimating Detection (Data-Array)
##

      for (y in minY[r]:Y) {
        for (k in 1:K[j,y]) {

          logit(p[j,k,y,i,r]) <- b0[i,r] + b1[i,r]*JDay[j,k,y] + b2[i,r]*(JDay[j,k,y]^2) + eta[y]
          X[j,k,y,i,r] ~ dbern(p[j,k,y,i,r]*Z[j,y,i,r])

        } #k
      } #y
    } #j
  } #i
} #r

##
#### Generating Missing Covariate Data
##

for (r in 1:R) {
  for (j in minJ[r]:maxJ[r]) {
    for (y in minY[r]:Y) {

      Site_area[j,y] ~ dnorm(0, 1)
      Cond[j,y] ~ dnorm(0, 1)

      for (k in 1:K[j,y]) {

        JDay[j,k,y] ~ dnorm(0, 1)

      } #k
    } #y
  } #j
} #r

#########
```

```
## Part -  Derived Parameters
#########


##
#### Estimating mean occupancy and detection rates of observed species (and their corresponding intercepts)
##


for(r in 1:R) {
  for(i in 1:I) {
    for(y in minY[r]:Y) {

      psi.avg[y,i,r] <- mean(psi[minJ[r]:maxJ[r],y,i,r])

    } #y
  } #i
} #r

##
#### Estimating region-level species richness
##

for(r in 1:R) {

  Npark[r] <- sum(W[,r])

} #r

##
#### Estimating site-level species richness by year
##

for(r in 1:R) {
  for (j in minJ[r]:maxJ[r]) {
    for (y in minY[r]:Y) {

      nSite[j,y] <- sum(Z[j,y,,r])

    } #y
  } #j
} #r


for(r in 1:R) {
  for (y in minY[r]:Y) {

   Nsite.avg[r,y] <- mean(nSite[minJ[r]:maxJ[r],y])

    } #y
} #r



#########
```

```
## Part -  END
#########

} #model
```

BIBLIOGRAPHY

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Adams, M. J., & Muths, E. (2019). Conservation research across scales in a national program: How to be relevant to local management yet general at the same time. *Biological Conservation*, *236*, 100-106.

Albert, C. H., Yoccoz, N. G., Edwards Jr, T. C., Graham, C. H., Zimmermann, N. E., & Thuiller, W. (2010). Sampling in ecology and evolution–bridging the gap between theory and practice. *Ecography*, *33*(6), 1028-1037.

Armsworth, P. R., Benefield, A. E., Dilkina, B., Fovargue, R., Jackson, H. B., Le Bouille, D., & Nolte, C. (2020). Allocating resources for land protection using continuous optimization: Biodiversity conservation in the United States. *Ecological Applications*, *30*(6), e02118.

Armsworth, P. R., Larson, E. R., Jackson, S. T., Sax, D. F., Simonin, P., Blossey, B., Green, N., Klein, M. L., Lester, L., Ricketts, T. H., & Runge, M. C. (2015). Are conservation organizations configured for effective adaptation to global change?. *Frontiers in Ecology and the Environment*, *13*(3), 163-169.

Baum, S. D., & Easterling, W. E. (2010). Space-time discounting in climate change adaptation. *Mitigation and Adaptation Strategies for Global Change*, *15*(6), 591-609.

Beaudrot, L., Ahumada, J. A., O'Brien, T., Alvarez-Loayza, P., Boekee, K., Campos-Arceiz, A., ... & Andelman, S. J. (2016). Standardized assessment of biodiversity trends in tropical forest protected areas: the end is not in sight. *PLoS Biology*, *14*(1), e1002357.

Bennett, J. R., Maxwell, S. L., Martin, A. E., Chadès, I., Fahrig, L., & Gilbert, B. (2018). When to monitor and when to act: Value of information theory for multiple management units and limited budgets. *Journal of Applied Ecology*, *55*(5), 2102-2113.

Berardo, R., & Lubell, M. (2019). The ecology of games as a theory of polycentricity: recent advances and future challenges. *Policy Studies Journal*, *47*(1), 6-26.

Blanchet, F. G., Cazelles, K., & Gravel, D. (2020). Co-occurrence is not evidence of ecological interactions. *Ecology Letters*, *23*(7), 1050-1063.

Boulinier, T., Nichols, J. D., Sauer, J. R., Hines, J. E., & Pollock, K. H. (1998). Estimating species richness: the importance of heterogeneity in species detectability. *Ecology*, *79*(3), 1018-1028.

Butchart, S. H., Walpole, M., Collen, B., Van Strien, A., Scharlemann, J. P., Almond, R. E., ... & Watson, R. (2010). Global biodiversity: indicators of recent declines. *Science*, *328*(5982), 1164-1168.

Buxton, R. T., Avery-Gomm, S., Lin, H. Y., Smith, P. A., Cooke, S. J., & Bennett, J. R. (2020). Half of resources in threatened species conservation plans are allocated to research and monitoring. *Nature Communications*, *11*(1), 1-8.

Callahan, J. T. (1984). Long-term ecological research. *BioScience*, *34*(6), 363-367.

Cash, D. W., Adger, W. N., Berkes, F., Garden, P., Lebel, L., Olsson, P., Pritchard, L. & Young, O. (2006). Scale and cross-scale dynamics: governance and information in a multilevel world. *Ecology and Society*, *11*(2).

Carlson, M., & Schmiegelow, F. (2002). Cost-effective sampling design applied to large-scale monitoring of boreal birds. *Conservation Ecology*, *6*(2).

Convention on Biological Diversity (2010). Strategic Plan for Biodiversity (2011-2020) and the Aichi Biodiversity Targets.

Crowder, L. B., Osherenko, G., Young, O. R., Airamé, S., Norse, E.A., Baron, N., Day, J. C., Douvere, F., Ehler, C. N., Halpern, B. S., & Langdon, S. J. (2006). Resolving mismatches in US ocean governance. *Science, 313*(5787), 617-618.

Cushman, S. A. (2006). Effects of habitat loss and fragmentation on amphibians: a review and prospectus. *Biological Conservation*, *128*(2), 231-240.

Díaz, S., Settele, J., Brondízio, E. S., Ngo, H. T., Agard, J., Arneth, A., ... & Zayas, C. N. (2019). Pervasive human-driven decline of life on Earth points to the need for transformative change. *Science*, *366*(6471).

Dietz, T., Ostrom, E., and Stern, P.C., 2003. The struggle to govern the commons. *Science*, *302*(5652), 1907-1912.

Dobbie, M. J., Henderson, B. L., & Stevens Jr, D. L. (2008). Sparse sampling: spatial design for monitoring stream networks. *Statistics Surveys*, *2*, 113-153.

Dorazio, R. M., & Royle, J. A. (2005). Estimating size and composition of biological communities by modeling the occurrence of species. *Journal of the American Statistical Association*, *100*(470), 389-398.

Dorazio, R. M., Royle, J. A., Söderström, B., & Glimskär, A. (2006). Estimating species richness and accumulation by modeling species occurrence and detectability. *Ecology*, *87*(4), 842-854.

Dorazio, R. M., Kery, M., Royle, J. A., & Plattner, M. (2010). Models for inference in dynamic metacommunity systems. *Ecology*, *91*(8), 2466-2475.

Ernstson, H., Sörlin, S., & Elmqvist, T. (2008). Social movements and ecosystem services—the role of social network structure in protecting and managing urban green areas in Stockholm. *Ecology and Society*, *13*(2).

Eyre, T. J., Fisher, A., Hunt, L. P., & Kutt, A. S. (2011). Measure it to better manage it: a biodiversity monitoring framework for the Australian rangelands. *The Rangeland Journal*, *33*(3), 239-253.

Fancy, S. G., Gross, J. E., & Carter, S. L. (2009). Monitoring the condition of natural resources in US national parks. *Environmental Monitoring and Assessment*, *151*(1), 161-174.

Field, S. A., Tyre, A. J., & Possingham, H. P. (2005). Optimizing allocation of monitoring effort under economic and observational constraints. *The Journal of Wildlife Management*, *69*(2), 473-482.

Frederick, S., Loewenstein, G., & O'donoghue, T. (2002). Time discounting and time preference: A critical review. *Journal of Economic Literature*, *40*(2), 351-401.

Game, E. T., Meijaard, E., Sheil, D., & McDonald-Madden, E. (2014). Conservation in a wicked complex world; challenges and solutions. *Conservation Letters*, *7*(3), 271-277.

Gerber, L. R. (2016). Conservation triage or injurious neglect in endangered species recovery. *Proceedings of the National Academy of Sciences*, *113*(13), 3563-3566.

Gelman, A., & Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, *7*(4), 457-472.

Gelman, A., & Shirley, K. (2011). Inference from simulations and monitoring convergence. In S., Brooks, Gelman A., Jones G. L., Meng X. L. (Eds.), Handbook of Markov Chain Monte Carlo (pp. 163-174). Boca Raton, FL: CRC Press.

Government Performance and Results Act of 1993, Pub. L. No. 103-62.

Grant, E. H. C., & Brand A. B. (2012). National capital region network amphibian monitoring protocol: revision 1.4 10 January 2012. Natural Resource Technical Report. National Park Service, Fort Collins, Colorado, USA.

Grant, E.H.C., Miller, D.A., Schmidt, B.R., Adams, M.J., Amburgey, S.M., Chambert, T., Cruickshank, S.S., Fisher, R.N., Green, D.M., Hossack, B.R. and Johnson, P.T., 2016. Quantitative evidence for the effects of multiple drivers on continental-scale amphibian declines. *Scientific Reports*, *6*(1), pp.1-9.

Grant, E. H. C., Zipkin, E. F., Nichols, J. D., & Campbell, J. P. (2013). A strategy for monitoring and managing declines in an amphibian community. *Conservation Biology*, *27*(6), 1245-1253.

Guillera-Arroita, G., Ridout, M. S., & Morgan, B. J. (2010). Design of occupancy studies with imperfect detection. *Methods in Ecology and Evolution*, *1*(2), 131-139.

Gunderson, L. H., Cosens, B., & Garmestani, A. S. (2016). Adaptive governance of riverine and wetland ecosystem goods and services. *Journal of Environmental Management*, *183*, 353-360.

Hayhoe, K., Wake, C. P., Huntington, T. G., Luo, L., Schwartz, M. D., Sheffield, J., Wood, E., Anderson, B., Bradbury, J., DeGaetano, A., and Troy, T. J. (2007). Past and future changes in climate and hydrological indicators in the US Northeast. *Climate Dynamics*, *28*(4), 381-407.

Heffernan, J. B., Soranno, P. A., Angilletta, M. J., Buckley, L. B., Gruner, D. S., Keitt, T. H., Kellner, J. R., Kominoski, J. S., Rocha, A.V., Xiao, J., & Harms, T. K. (2014). Macrosystems ecology: understanding ecological patterns and processes at continental scales. *Frontiers in Ecology and the Environment*, *12*(1), 5-14.

Hof, C., Araújo, M. B., Jetz, W., & Rahbek, C. (2011). Additive threats from pathogens, climate and land-use change for global amphibian diversity. *Nature*, *480*(7378), 516-519.

Johnson, C. N., Balmford, A., Brook, B. W., Buettel, J. C., Galetti, M., Guangchun, L., & Wilmshurst, J. M. (2017). Biodiversity losses and conservation responses in the Anthropocene. *Science*, *356*(6335), 270-275.

Jones, J. P. (2011). Monitoring species abundance and distribution at the landscape scale. *Journal of Applied Ecology*, *48*(1), 9-13.

Kao, R. H., Gibson, C. M., Gallery, R. E., Meier, C. L., Barnett, D. T., Docherty, K. M., ... & Schimel, D. (2012). NEON terrestrial field observations: designing continental-scale, standardized sampling. *Ecosphere*, *3*(12), 1-17.

Keller, M., Schimel, D. S., Hargrove, W. W., & Hoffman, F. M. (2008). A continental strategy for the National Ecological Observatory Network. *Frontiers in Ecology and the Environment*, *6*(5), 282-284.

Kellner, K. (2015). jagsUI: a wrapper around rjags to streamline JAGS analyses. R package version 1.1.

Kéry, M., & Royle, J. A. (2015). *Applied Hierarchical Modeling in Ecology: Analysis of distribution, abundance and species richness in R and BUGS: Volume 1: Prelude and Static Models*. Academic Press.

Leclère, D., Obersteiner, M., Barrett, M., Butchart, S. H., Chaudhary, A., De Palma, A., DeClerck, F. A., Di Marco, M., Doelman, J. C., Dürauer, M., & Freeman, R. (2020). Bending the curve of terrestrial biodiversity needs an integrated strategy. *Nature*, *585*(7826), 551-556.

Lindenmayer, D. B., & Likens, G. E. (2010). The science and application of ecological monitoring. *Biological Conservation*, *143*(6), 1317-1328.

Lookingbill, T. R., Schmit, J. P., Tessel, S. M., Suarez-Rubio, M., & Hilderbrand, R. H. (2014). Assessing national park resource condition along an urban–rural gradient in and around Washington, DC, USA. *Ecological Indicators*, *42*, 147-159.

Lubell, M. (2013). Governing institutional complexity: The ecology of games framework. *Policy Studies Journal*, *41*(3), 537-559.

MacKenzie, D. I., & Royle, J. A. (2005). Designing occupancy studies: general advice and allocating survey effort. *Journal of Applied Ecology*, *42*(6), 1105-1114.

MacKenzie, D. I., Nichols, J. D., Lachman, G. B., Droege, S., Andrew Royle, J., & Langtimm, C. A. (2002). Estimating site occupancy rates when detection probabilities are less than one. *Ecology*, *83*(8), 2248-2255.

Martin, J., Fackler, P. L., Nichols, J. D., Lubow, B. C., Eaton, M. J., Runge, M. C., ... & Langtimm, C. A. (2011). Structured decision making as a proactive approach to dealing with sea level rise in Florida. *Climatic Change*, *107*(1), 185-202.

Mattfeldt, S. D., Bailey, L. L., & Grant, E. H. C. (2009). Monitoring multiple species: estimating state variables and exploring the efficacy of a monitoring program. *Biological Conservation*, *142*(4), 720-737.

McDaniels, T., Longstaff, H., & Dowlatabadi, H. (2006). A value-based framework for risk management decisions involving multiple scales: a salmon aquaculture example. *Environmental Science & Policy*, *9*(5), 423-438.

McDonald, T. L. (2003). Review of environmental monitoring methods: survey designs. *Environmental Monitoring and Assessment*, *85*(3), 277-292.

Michaels, S., & Tyre, A. J. (2012). How indeterminism shapes ecologists' contributions to managing socio-ecological systems. *Conservation Letters, 5*(4), 289-295.

Mills, M., Álvarez-Romero, J. G., Vance-Borland, K., Cohen, P., Pressey, R. L., Guerrero, A. M., & Ernstson, H. (2014). Linking regional planning and local action: Towards using social network analysis in systematic conservation planning. *Biological Conservation*, *169*, 6-13.

Muths, E., Chambert, T., Schmidt, B. R., Miller, D. A. W., Hossack, B. R., Joly, P., Grolet, O., Green, D. M., Pilliod, D. S., Cheylan, M., & Fisher, R. N. (2017). Heterogeneous responses of temperate-zone amphibian populations to climate change complicates conservation planning. *Scientific Reports*, *7*(1), 1-10.

National Environmental Policy Act of 1969, Pub. L. No. 91-190.

National Park Service (2005). Long-term monitoring plan for natural resources in the National Capitol Region Network. Inventory and Monitoring Program, Center for Urban Ecology. Washington D. C.

National Parks Omnibus Management Act of 1998, Pub. L. No. 105-391.

Nicol, S., Brazill-Boast, J., Gorrod, E., McSorley, A., Peyrard, N., & Chadès, I. (2019). Quantifying the impact of uncertainty on threat management for biodiversity. *Nature Communications*, *10*(1), 1-14.

Nichols, J. D., & Williams, B. K. (2006). Monitoring for conservation. *Trends in Ecology & Evolution*, *21*(12), 668-673.

Olsen, A. R., Sedransk, J., Edwards, D., Gotway, C. A., Liggett, W., Rathbun, S., ... & Yyoung, L. J. (1999). Statistical issues for monitoring ecological and natural resources in the United States. *Environmental Monitoring and Assessment*, *54*(1), 1-45.

Ostrom, E. (2010). Polycentric systems for coping with collective action and global environmental change. *Global Environmental Change*, *20*(4), 550-557.

Perrings, C., & Hannon, B. (2001). An introduction to spatial discounting. *Journal of Regional Science*, *41*(1), 23-38.

Plummer, M. (2003). JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling. *Proceedings of the 3rd International Workshop on Distributed Statistical Computing*, *124*, 1-10.

Pollock, K. H., Nichols, J. D., Simons, T. R., Farnsworth, G. L., Bailey, L. L., & Sauer, J. R. (2002). Large scale wildlife monitoring studies: statistical methods for design and analysis. *Environmetrics*, *13*(2), 105-119.

Pounds, J. A. (2001). Climate and amphibian declines. *Nature*, *410*(6829), 639-640.

Reed, J., Van Vianen, J., Deakin, E. L., Barlow, J., & Sunderland, T. (2016). Integrated landscape approaches to managing social and environmental issues in the tropics: learning from the past to guide the future. *Global Change Biology*, *22*(7), 2540-2554.

Richgels, K. L., Russell, R. E., Adams, M. J., White, C. L., & Grant, E. H. C. (2016). Spatial variation in risk and consequence of Batrachochytrium salamandrivorans introduction in the USA. *Royal Society Open Science*, *3*(2), 150616.

Robinson, K. F., Fuller, A. K., Hurst, J. E., Swift, B. L., Kirsch, A., Farquhar, J., Decker, D. J., & Siemer, W. F. (2016). Structured decision making as a framework for large-scale wildlife harvest management decisions. *Ecosphere*, *7*(12), e01613.

Sanderlin, J. S., Block, W. M., & Ganey, J. L. (2014). Optimizing study design for multi-species avian monitoring programmes. *Journal of Applied Ecology*, *51*(4), 860-870.

Sauer, J. R., Link, W. A., Fallon, J. E., Pardieck, K. L., & Ziolkowski, D. J. (2013). The North American breeding bird survey 1966–2011: summary analysis and species accounts. *North American Fauna*, *79*, 1-32.

Sauer, J. R., Pardieck, K. L., Ziolkowski Jr, D. J., Smith, A. C., Hudson, M. A. R., Rodriguez, V., ... & Link, W. A. (2017). The first 50 years of the North American breeding bird survey. *The Condor: Ornithological Applications*, *119*(3), 576-593.

Saunders, S. P., Farr, M. T., Wright, A. D., Bahlai, C. A., Ribeiro Jr, J. W., Rossman, S., ... & Zipkin, E. F. (2019). Disentangling data discrepancies with integrated population models. *Ecology*, *100(*6), e02714.

Scarlett, L., & McKinney, M. (2016). Connecting people and places: the emerging role of network governance in large landscape conservation. *Frontiers in Ecology and the Environment*, *14*(3), 116-125.

Scholes, R. J., Mace, G. M., Turner, W., Geller, G. N., Jürgens, N., Larigauderie, A., ... & Mooney, H. A. (2008). Toward a global biodiversity observing system. *Science*, *321*(5892), 1044-1045.

Schreuder, H. T., Ernst, R., & Ramirez-Maldonado, H. (2004). Statistical techniques for sampling and monitoring natural resources. General Technical Report RMRS-GTR-126. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station.

Sparrow, B. D., Edwards, W., Munroe, S. E., Wardle, G. M., Guerin, G. R., Bastin, J. F., ... & Lowe, A. J. (2020). Effective ecosystem monitoring requires a multi-scaled approach. *Biological Reviews*, *95*(6), 1706-1719.

Stadt, J. J., Schieck, J., & Stelfox, H. A. (2006). Alberta Biodiversity Monitoring Program–monitoring effectiveness of sustainable forest management planning. *Environmental Monitoring and Assessment*, *121*(1), 33-46.

Stewart, W.P., Williams, D.R. and Kruger, L.E. (Eds.). (2013). *Place-based conservation: Perspectives from the social sciences*. Springer.

Stottlemyer, R. (1987). External threats to ecosystems of US national parks. *Environmental Management*, *11*(1), 87-89.

Stuart, S. N., Chanson, J. S., Cox, N. A., Young, B. E., Rodrigues, A. S., Fischman, D. L., & Waller, R. W. (2004). Status and trends of amphibian declines and extinctions worldwide. *Science*, *306*(5702), 1783-1786.

Sutherland, C., Brambilla, M., Pedrini, P., & Tenan, S. (2016). A multiregion community model for inference about geographic variation in species richness. *Methods in Ecology and Evolution*, *7*(7), 783-791.

Sutherland, W. J., Pullin, A. S., Dolman, P. M., & Knight, T. M. (2004). The need for evidence-based conservation. *Trends in Ecology & Evolution*, *19*(6), 305-308.

Tallies et al. (In Review). Prioritizing actions: spatial action maps for conservation. *Annals of the New York Academy of Sciences.*

Thompson, S. K., Wilks, S., & Shewhart, W. (2012). Stratified sampling. *Sampling; Wiley Series in Probability and Statistics*, 139-156.

Thorpe, A. S., Barnett, D. T., Elmendorf, S. C., Hinckley, E. L. S., Hoekman, D., Jones, K. D., LeVan, K. E., Meier, C. L., Stanish, L. F. & Thibault, K. M. (2016). Introduction to the sampling designs of the national ecological observatory network terrestrial observation system. *Ecosphere*, *7*(12), e01627.

Tilman, D., Clark, M., Williams, D. R., Kimmel, K., Polasky, S., & Packer, C. (2017). Future threats to biodiversity and pathways to their prevention. *Nature*, *546*(7656), 73-81.

Tittensor, D. P., Walpole, M., Hill, S. L., Boyce, D. G., Britten, G. L., Burgess, N. D., ... & Ye, Y. (2014). A mid-term analysis of progress toward international biodiversity targets. *Science*, *346*(6206), 241-244.

Wintle, B. A., Runge, M. C., & Bekessy, S. A. (2010). Allocating monitoring effort in the face of unknown unknowns. *Ecology Letters*, *13*(11), 1325-1337.

Wright, A. D., Bernard, R. F., Mosher, B. A., O'Donnell, K. M., Braunagel, T., DiRenzo, G. V., Fleming, J., Shafer, C., Brand, A. B., Zipkin, E. F., & Grant, E. H. C. (2020a). Moving from decision to action in conservation science. *Biological Conservation*, *249*, 108698.

Wright, A. D., Grant, E. H. C., & Zipkin, E. F. (2020b). A hierarchical analysis of habitat area, connectivity, and quality on amphibian diversity across spatial scales. *Landscape Ecology*, *35*(2), 529-544.

Wyborn, C., & Bixler, R. P. (2013). Collaboration and nested environmental governance: scale dependency, scale framing, and cross-scale interactions in collaborative conservation. *Journal of Environmental Management*, *123*, 58-67.

Yoccoz, N. G., Nichols, J. D., & Boulinier, T. (2001). Monitoring of biological diversity in space and time. *Trends in Ecology & Evolution*, *16*(8), 446-453.

Ziolkowski, D., Pardieck, K., & Sauer, J. R. (2010). On the road again for a bird survey that counts. *Birding*, *42*(4), 32-41.

Zipkin, E. F., Grant, E. H. C., & Fagan, W. F. (2012). Evaluating the predictive abilities of community occupancy models using AUC while accounting for imperfect detection. *Ecological Applications*, *22*(7), 1962-1972.

Zipkin, E. F., Zylstra, E. R., Wright, A. D., Saunders, S. P., Finley, A. O., Dietze, M. C., Itter, M. S. and Tingley, M. W. (2021). Addressing data integration challenges to link ecological processes across scales. *Frontiers in Ecology and the Environment*, *19*(1), 30-38.

Zipkin, E. F., Royle, J. A., Dawson, D. K., & Bates, S. (2010). Multi-species occurrence models to evaluate the effects of conservation and management actions. *Biological Conservation*, *143*(2), 479-484.