Environ Monit Assess (2019) 191: 597
https://doi.org/10.1007/s10661-019-7759-7

Optimizations for time and effort in long-term monitoring: a case study using a multidecadal terrestrial salamander monitoring program

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Received: 14 March 2019 / Accepted: 13 August 2019 / Published online: 28 August 2019

Abstract Long-term monitoring programs can identify environmental trends or reveal limitations to protocols, as long as their results are analysed appropriately. While monitoring programs are not necessarily hypothesis-driven, their data are important for conservation and can guide improvements to monitoring programs. Here, we present a case study using dynamic occupancy models to guide the optimization of time and effort in a long-term terrestrial salamander monitoring program. To ensure a detailed analysis, we analysed the available long-term data to first identify estimates of occupancy and detection parameters for the salamanders. Using these estimates, we created simulations to identify the optimal number of years for monitoring and the optimal allocation of spatial and temporal survey replicates. Our data support previous claims that monitoring programs should be allowed to run for at least a decade. We also found that in order to obtain accurate estimates of species occupancy, programs should consider appropriate partitioning of monitoring effort across spatial and temporal scales. We show how analyses of long-term monitoring datasets are valuable not only for trend detection but also for the development of templates to guide the design and optimization of similar programs.

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Keywords Plethodontid · Dynamic occupancy models · Coverboard · Adaptive monitoring · Optimization · Survey allocation

Introduction

The growing threats to biodiversity from human activities, including habitat alterations and climate change, have been accompanied by an increased demand for long-term environmental monitoring (Urban et al. 2016; McMahon et al. 2011). Long-term monitoring is needed to understand complex population dynamics, so that conclusions can be made about the state of a particular system. Monitoring is often used for two reasons: to determine the effectiveness of conservation management and to inform future management through identifying and understanding the reasons for ecosystem degradation. Some monitoring programs have acquired decades worth of data (Lindenmayer et al. 2012), and these data not only provide information about the system in question but are also as a valuable resource to guide future monitoring. While large studies looking at multiple programs have been imperative to understanding reoccurring patterns in monitoring programs (White 2019; Rhodes and Jonzén 2011; MacKenzie and Royle 2005), case-specific analyses of monitoring data can provide a more detailed understanding of how best to monitor similar systems in the future.

Researchers have argued for more rigorous decision-making processes during the design of monitoring programs (Lindenmayer and Likens 2009; Caughlan and

Oakley 2001). In many cases, monitoring design has focussed on data collection, giving less consideration to the analysis and presentation of the data (Field et al. 2007; Lindenmayer and Likens 2009). Proper statistical consideration can ensure time and money are spent on data that can be interpreted in the context of the goals of the monitoring program. While the choice of statistical analysis is intrinsically related to the type of data collected, program-specific considerations of statistical power and survey optimization are also important to the success and cost effectiveness of the program. In particular, White (2019) found that the number of years required for sufficient statistical power varies greatly between monitoring systems, reasoning against the use of conventional rules-of-thumb. Similarly, with regard to the precision of trend estimates, the optimal allocation of sampling effort over time and space has been shown to depend on the dynamics of the chosen system (Rhodes and Jonzén 2011).

Even with careful consideration of all aspects of the chosen monitoring system, program designs often need to be updated once the data reveal more about the specific nature of the system. Adaptive monitoring sees aspects of monitoring as an iterative process, where information gained through monitoring guides the evolution of new questions, designs, and analyses (Lindenmayer and Likens 2009). These principles are particularly relevant to long-term monitoring programs, where information on indicator species have been collected for many years in exactly the same fashion, and which can provide a more complete picture of species dynamics and factors that may influence population fluctuations (Kéry et al. 2009; Magurran et al. 2010).

In this paper, we present a case study using data from a terrestrial salamander monitoring program (1999–2016) to show how detailed, program-specific analyses can improve how we approach the design and management of monitoring programs. Our main objective was to identify ways to optimize the time and effort required to accomplish monitoring goals. We identified long-term trends and predictors of short-term change in the salamander populations in order to construct realistic models for optimization. We investigated (i) the effect of the number of monitoring years on the reliability of trend detection and (ii) the effect of the number and allocation of survey replicates on the accuracy and precision of model estimates. The terrestrial salamander monitoring program used in this study uses a replicate survey design to account for imperfect detection. Surveys with imperfect detection are likely to be biased over time in their estimates of population parameters. As such, our approach to optimization expands upon previous studies by using estimates of detection probability to adjust final optimizations. We show how analyses of valuable long-term monitoring datasets, spanning almost two decades of continuous monitoring, can be used to improve the efficiency of the monitoring program and to develop a template for other monitoring programs using similar replicate survey designs.

Methods

Monitoring program design

The terrestrial salamander monitoring dataset used in this study was collected by the Long Point World Biosphere Reserve (LPBR) as part of the Environmental Monitoring and Assessment Network (EMAN). The aim of EMAN is to improve understanding of changes in various Canadian ecosystems through long-term monitoring. The red-backed salamander (*Plethodon cinereus*) was the species of interest for this monitoring program. Plethodontid salamanders have been identified as important indicator species for long-term monitoring due to their high abundance in forests, high detectability, large geographic range, sensitivity to environmental disturbances, and importance in the forest food web (Welsh and Hodgson 2013).

Two forest tracts within LPBR, Backus Woods and Wilson Forest Tract, were surveyed as part of the program. Backus is an old-growth forest while Wilson has been subject to periodic timber extraction. Both tracts are Maple-dominant Mixed Wood Carolinian Forests and have remained relatively unimpacted over the course of the monitoring program. Single square plots (10 km^2) within the interior of each forest were used for the coverboard monitoring project (Fig. 1). Along the perimeter of each square plot, 160 artificial coverboards were placed in two parallel rows of 80 boards each. The square plots were originally set up to act as reference plots for a tree health monitoring program. Unlike the tree health monitoring program, we did not assume that salamander abundances in the square plots were representative of the entire forest tract. Coverboards were surveyed for the presence of salamanders no more than once weekly (to minimize biases due to repeated disturbance (Marsh and Goicochea 2003)) in the spring

(March to June) and fall (August to October) from 1999 to 2016 inclusive. Corresponding daily and annual precipitation and temperature data were obtained from a weather station located approximately 25 km northeast of the forest plots and gap-filled using an approach similar to Wei and McGuinness (1973).

Trend analysis

To analyse trends in the monitoring data, we used dynamic occupancy models developed by Mackenzie et al. (2003). False negatives are common in coverboard surveys because salamanders may not be found under the coverboard at the time of the survey (temporarily buried underground or away from the coverboard foraging) even though they normally reside there. Dynamic occupancy models estimate annual occupancy using repeated measures to account for biases from imperfect detection. They allow for estimates of λ_{ij} (probability of salamander occupancy at board i in year j), p_{ijk} (probability of detection at board i, in survey k of year j, given salamanders are present), γ_{ij} (probability that unoccupied board i in year j is colonized in year $j+1$), and ε_{ij} (probability that occupied board i in year j becomes unoccupied in year $j+1$). It is important to note that multiple salamanders are often found under individual boards. For models where multiple individuals inhabit a single board, occupancy refers to the probability that at least one salamander is present during a sampling period while detection refers to the probability that at least one of the salamanders occupying the board is present at the time of the survey.

Dynamic occupancy models assume closure for board occupancy within survey periods. Since plethodontids have small home ranges and do not move more than a few meters throughout the active season (Petranka 1998), it is unlikely that the assumption of closure would be violated during the survey period. In exceptionally wet springs, some coverboards were flooded during the start of the survey period. Flooded boards are unable to be occupied by the terrestrial salamanders, but observations of instances of flooding were originally unforeseen and not fully recorded in the dataset. Consequently, we needed to account for artificial decreases in occupancy estimates from spring flooding and developed separate models for spring and fall monitoring periods.

We used covariates in our models to reduce the number of required parameter estimates and to determine if there were any relationships between meteorological conditions and plethodontid occupancy dynamics. In dynamic occupancy models, parameter estimates of detection, initial occupancy, colonization, and local extinction are functions of covariates on the logit scale. Dynamic occupancy models allow for the inclusion of three types of covariates: site-specific covariates, survey-specific covariates, and year-specific covariates. For all parameters, we included the site-specific covariate of forest plot. For detection probability (p_{ijk}), we also included the year-specific covariate of monitoring year, the survey-specific covariates of the presence of rain 24 h prior to the survey, and the linear and quadratic terms for average daily temperature. For the occupancy dynamics of colonization (γ_{ij}) and local extinction (ε_{ij}), we included the year-specific covariates of annual rainfall (April–October), spring rainfall (March–June), average summer temperature (June–September), average winter temperature (December–March), and the year that monitoring was conducted (monitoring year). The spring rainfall covariate was used exclusively in the spring model as an index of flood intensity during the survey period. We ran all models using the program PRESENCE V12.10 (Hines 2006).

For each season, the top three models based on Quasi-Akaike's Information Criterion (QAIC) values were used to create weighted averages of the parameter estimates. Since board occupancy cannot be directly estimated from the model, we used the smoothing method described by Weir et al. (2009) to derive occupancy estimates for each year. The delta method was used to derive standard errors for all parameter estimates. To analyse trends in board occupancy across years, we fitted linear models for the plot-averaged occupancy estimates for each season. For each model, we included covariates for year and plot. To account for temporal autocorrelation in the occupancy estimates, we fitted our models using generalized least squares and specified a first-order correlation structure with year as the grouping variable. We used a similar strategy to analyse trends in detection probability, this time combining estimates from spring and fall into a single linear model and using year and season as covariates. For all analyses, we used a 95% level of significance to test for the importance of covariates.

Effect of monitoring length on trend detection

We simulated detection/non-detection data based on model averages to investigate the ability to detect declines

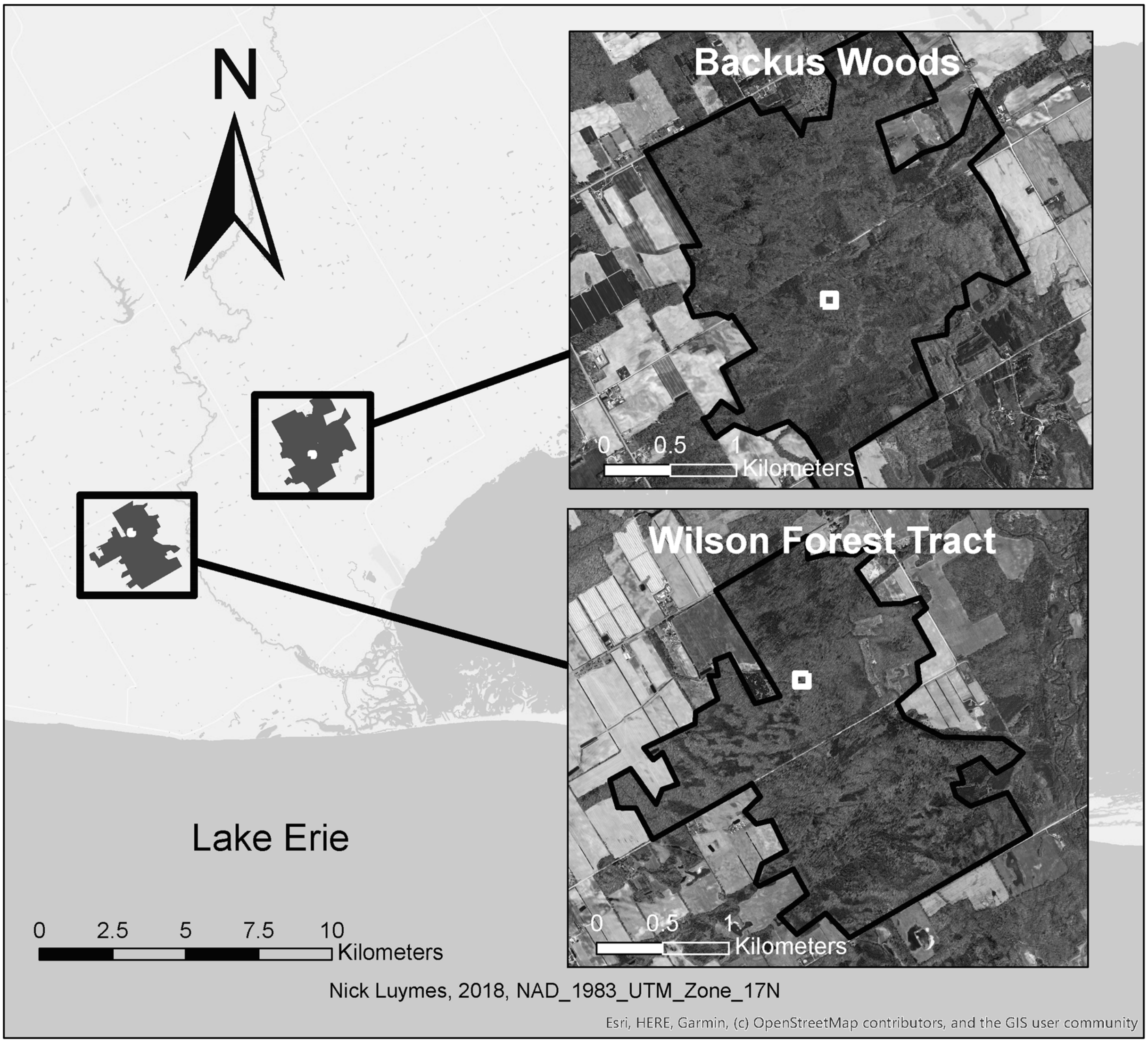

Fig. 1 Location of the EMAN plots. White squares represent the locations of EMAN plots used for the salamander monitoring program within Backus Woods and Wilson Forest Tract. Satellite imagery source: Ontario Ministry of Natural Resources and Forestry, South Western Orthophotography Project. Basemap source: ©OpenStreetMap contributors

in occupancy for different lengths of monitoring programs. For all simulation analyses, we used model averages from the fall data in order to mitigate any biases related to undocumented coverboard flooding in the spring. We ran simulations for declines ranging from 5 to 25% every 5 years and for monitoring periods ranging from 5 to 25 years. After the percent decline in occupancy was applied to each year, we allowed for additional fluctuations across years based on average year-to-year fluctuations observed in the monitoring results. We assumed that probability of colonization (γ_{ij}) and persistence ($1 - \varepsilon_{ij}$) was equal, to minimize the number of parameter estimates and to simplify calculations. Using the occupancy estimates from the simulated data, we fitted linear models with a year as the covariate and recorded whether the trend estimate was significantly less than zero. We plotted the number of simulations with significant decreasing trend estimates.

Effect of survey replicate allocation on occupancy estimates

To investigate the accuracy and precision of single-season occupancy estimates, we completed additional

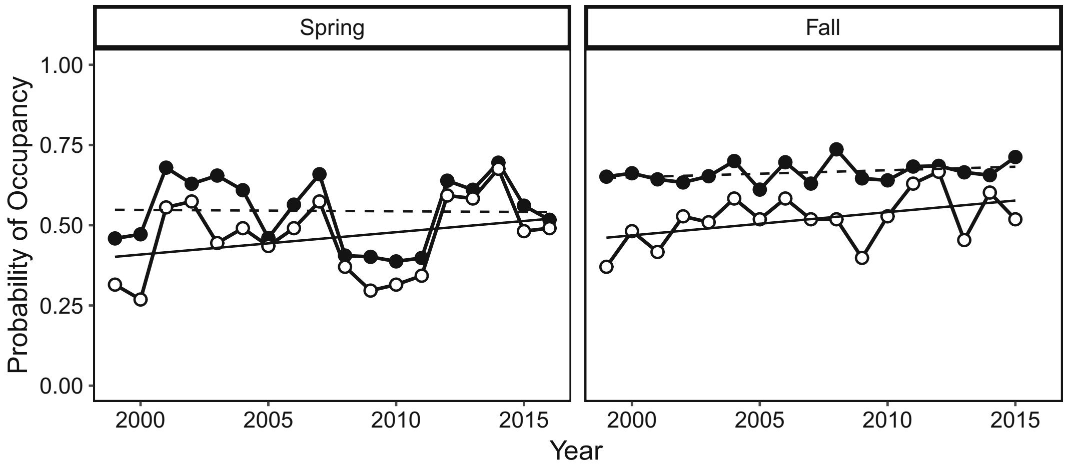

Fig. 2 Smoothed model estimates of the probability of occupancy for each season. Seasonal occupancy estimates for modelled (closed circles) and raw (open circles) estimates of both sites combined. Naïve estimates are based on the raw data and do not account for detection probabilities. Linear trendlines for modelled (solid lines) and raw (dashed lines) estimates are included for to highlight the absence of a long-term trend in occupancy

simulations using average detection and occupancy estimates from our models. For these simulations, we investigated the effect of the number of surveys, boards, and survey plots on the accuracy and precision of occupancy estimates. We ran simulations for a moderate degree of within-forest variability in board occupancy (similar to the variability observed in this study) and for a high degree of variability. We used 1000 simulations for each combination and plotted the average occupancy estimate and confidence bars that contained 95% of the occupancy estimates. We qualitatively compared the average estimates with the occupancy value used to create the simulated data. In all cases, we ran simulations in R (R Core Team 2017) using the unmarked package (Fiske and Chandler 2009).

Results

Trend analysis

During the 18 years of monitoring used for this analysis, a total of 369 surveys were completed: 212 (mean of 11.8) in the spring and 157 (mean of 9.2) in the fall. There were 4066 salamanders identified under coverboards during this period. On average, 117 (ranging from 45 to 213) salamanders were identified under coverboards in spring each year and 115 (ranging from 56 to 197) during the fall. Daily temperatures for the long point area averaged 12 °C during the survey periods (spring and fall), 19 °C during the summer, and − 3 °C during the winter.

Detection probabilities associated with the best models (i.e. with lowest AIC scores) covaried with sampling year, forest plot, occurrence of rain in the previous day, and the linear and quadratic terms for average daily temperature. Estimates of the dispersion parameter (c-hat) for the full models were 3.5 for spring and 1.7 for fall, indicating the presence of overdispersion. Using the c-hat estimates for model selections, initial occupancy for the best spring model (i.e. with the lowest QAIC score) covaried with site. The probability of colonization covaried with the amount of annual precipitation in the previous year, estimated occupancy in the previous year, and amount of spring precipitation during the survey period; the probability of extinction covaried with amount of annual precipitation in the previous year and average temperature during the previous summer (Table 1). By comparison, probability of colonization for the best fall model covaried with the amount of annual precipitation corresponding to the current year as well as estimated occupancy in the previous year, while the probability of extinction covaried with the amount of annual precipitation in the current year and the average temperature during the previous winter (Table 1).

Averages for the smoothed occupancy estimates across years were *0.55* ± 0.02 (± SE) for the spring and *0.66* ± 0.01 (± SE) for the fall. There was large variation in occupancy estimates for individual boards. For spring

Table 1 Quasi-Akaike's Information Criterion values (QAIC) for the top three ranked models, the full model, and the null model for each season. QAIC values are calculated using the dispersion parameter (c-hat) from the full model. The top three models are used to calculate weighted averages of the model parameters. The covariates for initial occupancy (ψ), colonization (γ), extinction (ε), and detection probability (p) are listed in brackets

Spring			
Model	**QAIC**	***w***	***K***
ψ (site), γ (annual precip., previous occ., spring precip.), ε (annual precip., summer temp.), p (year, site, rain, temp., temp.^{2})	3386.97	0.45	31
ψ (site), γ (annual precip., winter temp., previous occ.), ε (annual precip., summer temp.), p (year, site, rain, temp., temp.^{2})	3387.66	0.31	31
ψ (site), γ (annual precip., previous occ.), ε (annual precip., summer temp.), p (year, site, rain, temp., temp.^{2})	3388.19	0.24	32
ψ (site), γ (year), ε (year), p (model)	3431.19	0	58
ψ(), γ(), ε(), p (year, site, rain, temp., temp.^{2})	3389.60	0	25
Fall			
Model	**QAIC**	***w***	***K***
ψ(), γ (annual precip., previous occ.), ε (annual precip., winter temp.), p (year, site, rain, temp., temp.^{2})	6319.17	0.42	28
ψ(), γ (annual precip., previous occ.), ε (annual precip.), p (year, site, rain, temp., temp.^{2})	6319.87	0.38	27
ψ (site), γ (previous occ.), ε (annual precip., winter temp.), p (year, site, rain, temp., temp.^{2})	6321.20	0.20	27
ψ (site), γ (year), ε (year), p (year, site, rain, temp., temp.^{2})	6358.22	0	55
ψ(), γ(), ε(), p (year, site, rain, temp., temp.^{2})	6335.99	0	24

w, model weights; *K*, number of parameters

data, 10% of the coverboards were estimated to be occupied < 32% of the time while another 10% were estimated to be occupied > 80% of the time. Similarly, for the fall, 10% of the coverboards were estimated to be occupied < 43% of the time, while another 10% was estimated to be occupied > 90% of the time. Interannual variations in occupancy estimates were greater for spring than for fall (Fig. 2), with average annual changes of 16% for spring versus only 6% for the fall. There were no significant trends for occupancy estimates during the spring (slope = − 0.002, $p = 0.88$) or fall (slope = 0.011, $p = 0.15$).

Estimates of detection probability averaged *0.15* ± 0.01 (± SE) across years for the spring and *0.16* ± 0.01 (± SE) for the fall. Despite large fluctuations, mean annual estimates generally increased across years (slope = 0.046, $p < 0.001$; Fig. 3). Mean estimates (B_0) and slopes (B_1) for detection probability did not significantly differ between fall and spring ($\Delta B_0 = -0.10$, $p = 0.41$; $\Delta B_1 = 0.013$, $p = 0.58$). Both models appeared to show an initial increase in detection probability, followed by a decrease, and ending with another increase (Fig. 3).

Effect of monitoring length on trend detection

Results of our analysis for trend detection indicated that a survey conducted at 5-year intervals over a period of 10 years would have sufficient power (> 0.9) to detect a decline in occupancy of 20%; a survey conducted at 5-year intervals over a 15-year period would have sufficient power to determine a 10% decline, whereas a survey conducted at 5-year intervals over a 25-year period would be required to detect a 5% decline in occupancy (Fig. 4). These correspond to declines in occupancy of 36% over 10 years, 27% over 15 years, and 23% over 25 years. A decline approaching 60% would have been required to permit detection over a short survey period of only 5 years.

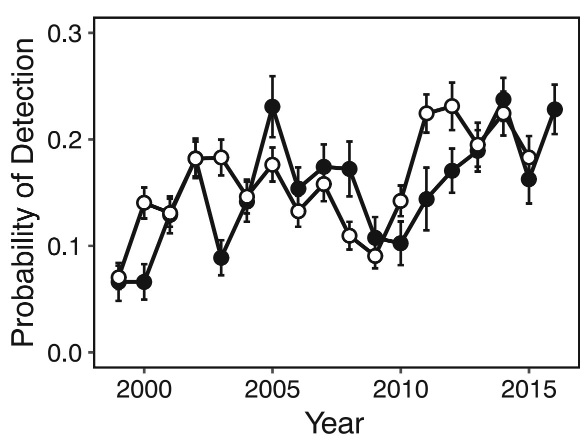

Fig. 3 Estimated probability of detection for spring (closed circles) and fall (open circles) of each year of the monitoring program

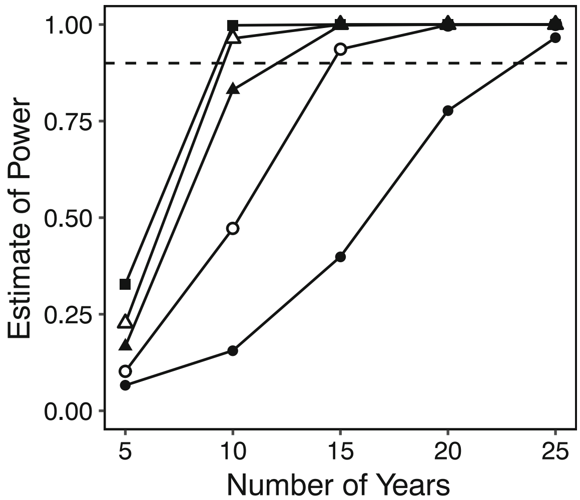

Fig. 4 Estimated power to detect declines in coverboard occupancy. Simulations for declines of 0.05 (closed circles), 0.10 (open circles), 0.15 (closed triangles), 0.20 (open triangles), and 0.25 (squares) every 5 years. Significance of the estimated slopes was assessed using an alpha of 0.05. The dotted horizontal line represents the chosen threshold for sufficient power (≥ 0.9). 1000 simulations were run for each unique combination

Effect of survey replicate allocation on occupancy estimates

Accuracy assessments indicated that accurate estimates of occupancy occur when survey designs include at least 10 survey sites and a combination of either 80 boards and 12 surveys or 160 boards and 8 surveys (Fig. 5). Increasing the number of boards or surveys past those values tends to have small effects on the precision of occupancy estimates. On the other hand, increases in the number of survey sites tended to have a more pronounced effect on the precision of occupancy estimates. Low numbers of boards, surveys, or sites, regardless of the magnitude of the other two parameters, tended to result in occupancy estimates with low accuracy and precision. Changes in the variability of occupancy estimates within the forest had little impact on the precision of occupancy estimates, and while accuracy was slightly different between treatments, this difference may be more related to the difficulty in estimating the central tendency of occupancy data.

Discussion

While occupancy fluctuated across years, our results did not show any significant decrease or increase in abundance through time, suggesting that populations in both plots have been stable over the monitoring period. Short-term fluctuations in occupancy appeared to be influenced by changes in annual meteorological conditions, supporting the role of moisture in plethodontid abundance (Warren II and Bradford 2010; Grover 1998). The original EMAN protocol for using salamander abundance as an index of environmental change recommended that "relative changes in abundance ….be determined after a few years of sampling" (Zorn et al. 2004; Environment Canada 2003). Given the observed large annual fluctuations in occupancy in a relatively undisturbed population, it would be unrealistic to expect abundances monitored over a few years to yield meaningful trends. For example, in our simulations, a program with fewer than 5 years of monitoring data would not be able to reliably detect the presence of a declining trend unless the population had been reduced by an unrealistically high rate of 60%. More realistic loss rates of 5 to 10% would require 15 to 25 years of monitoring. For this program and similar programs, we advise against conducting trend analysis with datasets < 10 years, since results may lead to incorrect conclusions on the status of the population.

Such a lack of statistical power in short-term trend analysis has been identified for other types of monitoring programs and indicator species (Erb et al. 2015; Nielsen et al. 2009; Helander et al. 2008; Meyer et al. 2010). At short timescales, the natural variation in the population parameters of interest tends to mask other, long-term changes that the system is experiencing. This has been shown more generally by White (2019) in their analysis of vertebrate data from 822 different populations. They found that roughly three-quarters of the populations they studied required 10 years of continuous monitoring data for trends to be reliably detected. Our results provide further justification for the need for > 10 years of monitoring and demonstrate the ability to determine program-specific thresholds for trend detection. Despite the pattern of unreliability for trend detection in short-term monitoring programs, there is considerable variation in the minimum time required for trend detection across monitoring programs (White 2019). As such, being able to conduct power analyses based on the specific characteristics of the monitoring system and chosen statistical analyses can provide more accurate estimates of the minimum number of years, thus saving time and resources.

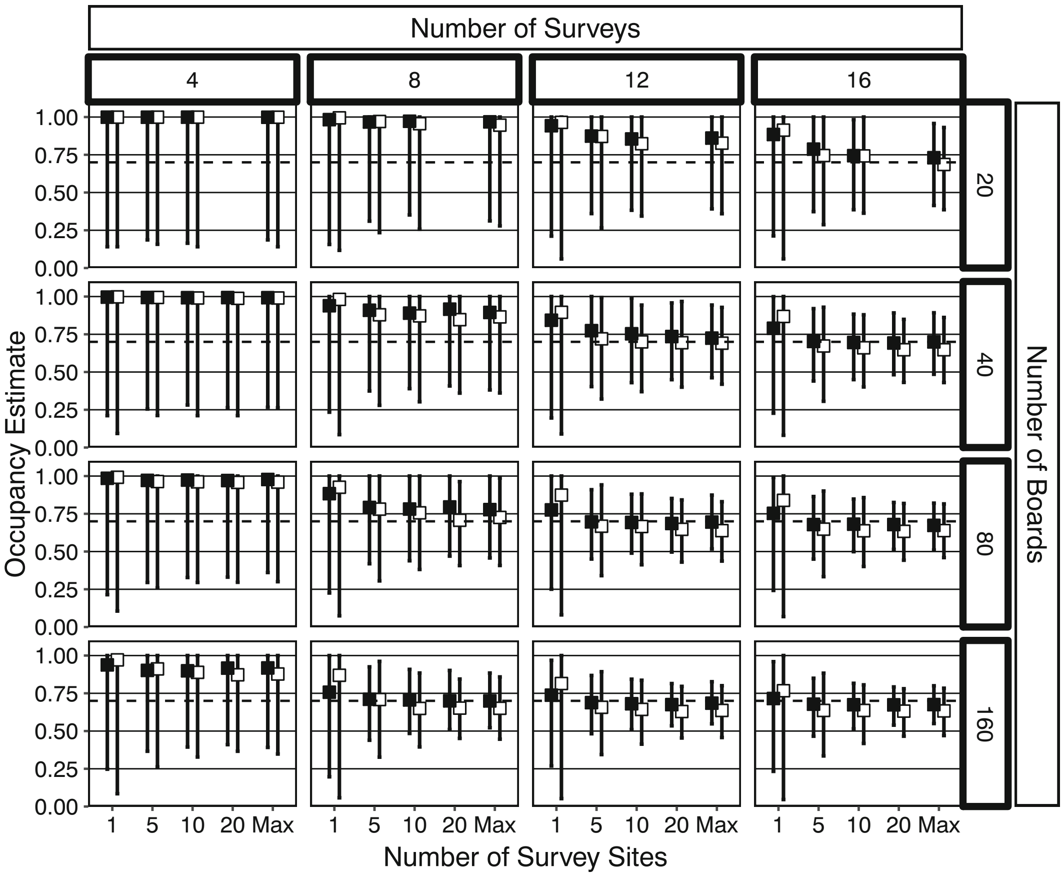

Fig. 5 Mean and 95% CI of single-year occupancy estimates based on simulated coverboard occupancy data. Simulations for a range of boards, surveys, and survey sites. The closed squares represent averages for simulations run with a moderate degree of within-forest variability in occupancy, whereas the open squares represent averages for simulations run with a high degree of variability. The maximum number of survey sites condition refers to simulations run with a survey site for every board. We omitted simulations with 20 boards and 20 survey sites to avoid repetition. 1000 simulations were run for each unique board-survey-site combination. The dotted line represents the true average occupancy value (0.7) for the forest

The quality of occupancy estimates needs to be considered alongside the number of monitoring years in order to conduct reliable trend analyses. In this study, large fluctuations in detection probability across years and surveys highlight the importance of a replicate survey design for adjusting occupancy estimates. We show that moderate numbers of spatial replicates (coverboards and survey sites) and temporal replicates (surveys) are required to accurately and precisely estimate occupancy. For example, a minimum of 160 boards split among 10 survey sites with 8 surveys per season is recommended for the monitoring program used in this case study. Low numbers of boards, surveys, or sites tend to result in estimates with low accuracy and precision regardless of the magnitude of the other two replicates. Our results suggest that effort should be partitioned across the monitoring parameters of surveys, boards, and sites to avoid the disproportionate effects associated with having a small number of any of these replicates.

Consideration must also be given to the limitations of the monitoring program when optimizing for design. For example, the number of surveys in any given year for the salamander monitoring program is limited by the number of weeks when salamanders are active. Since the number of appropriate weeks can change from year to year, a conservative approach should be taken when planning how many surveys will be conducted. Similarly, though distributing boards across a greater number of survey sites can improve the precision of occupancy estimates, it comes at a cost of increased sampling time.

How one partitions survey effort across temporal and spatial replicates is dependent on the dynamics of the populations used in the monitoring system, the environmental variation, and the magnitude of observation error (Rhodes and Jonzén 2011). Estimates of population parameters for populations with proportionally high spatial correlation will benefit from program designs with a larger emphasis on temporal replicates, and vice versa for populations with proportionally higher temporal correlation (Rhodes and Jonzén 2011). Due to the dependency of plethodontid salamanders on specific microhabitats (Petranka 1998), the monitoring program in this case study benefits more from high spatial replication of surveys. However, sufficient temporal replicates are necessary to offset low detection probabilities and minimize the errors associated with uncorrected occupancy estimates (Field et al. 2005).

Short-term data, in particular, is important for determining the dynamics of monitoring systems. As more information is gained on the monitoring system, program designs can be adjusted for high or low spatial and temporal correlation in populations. Even if the species of interest is well known, populations in different geographic regions can have different dynamics leading to different optimal survey designs (Petranka 1998). These adjustments are a key aspect of adaptive monitoring (Lindenmayer and Likens 2009) and, together with the refinement of program goals and questions, will be a necessary part of monitoring program development going forward.

Our research continues to address important questions related to how monitoring effort should be allocated to optimize the accuracy of parameter estimates and reliability of trend analyses. Researchers have pointed to the importance of considering monitoring program cost and effort in the context of program goals (McDonald-Madden et al. 2010; Reynolds et al. 2011; Caughlan and Oakley 2001). Given the small amount of resources allocated to conservation programs, optimizations for program design are increasingly being recognized as integral to the development and continued improvement of monitoring programs (McDonald-Madden et al. 2010). In particular, we have highlighted optimizations in the context of dynamic occupancy models, which represent a relatively recent development for long-term monitoring programs. We have shown that using dynamic occupancy models to account for detection probabilities in replicate survey designs can be important not only for trend analysis but also for the improvement of monitoring program design. We believe that a similar framework to the one used in this study can be applied to other monitoring programs that use replicate survey designs. There is considerable potential for future monitoring based on the infrastructure that has been created through long-term monitoring programs. Using these suggestions, monitoring programs can continue to provide the scientific community with extensive datasets that would otherwise be difficult to collect for researchers limited by short-term funding.

Acknowledgements We would like to thank all parties involved in the EMAN terrestrial salamander monitoring program at LPBR. We acknowledge Brian Craig for his dedicated work developing and maintaining the program over the years. We would also like to acknowledge all the personnel who conducted the weekly coverboard surveys over the years including volunteers Jim Wilson, who regularly monitored the cover boards for over 15 years, Nick Wilson, and Adam Chamberlin. We greatly appreciate the suggestions of two anonymous reviewers.

Compliance with ethical standards

Ethical approval All applicable international, national, and/or institutional guidelines for the care and use of animals were followed.

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