

A POWER ANALYSIS FOR THE USE OF COUNTS OF EGG MASSES TO MONITOR WOOD FROG (*LITHOBATES SYLVATICUS*) POPULATIONS

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Abstract.—Counts of numbers of egg masses have been proposed as a state variable for monitoring Wood Frog (*Lithobates sylvaticus*) populations, and some important benefits of this approach have been identified (e.g., low cost). If the power to detect trends in time series of numbers of egg masses is low, however, this approach may not be useful. We used computer simulation to evaluate the effects of several parameters on the statistical power of detecting trends in counts of numbers of egg masses. Results of the simulations indicate that a minimum of nine years of monitoring is necessary to have high statistical power (≥ 0.80) for detecting a 10% decline per year. For populations experiencing low rates of annual decline ($\leq 4\%$ annually), two decades or more of monitoring data are required to achieve high levels of power. Increasing the proportion of egg masses detected by surveyors results in only minor improvements in statistical power, while increasing the Type I error rate (α) results in greater improvements. Insufficient duration of financial and institutional support for collection of data is a common cause of failure in monitoring programs. The results of this study provide guidance regarding the necessary duration of monitoring programs for amphibian populations and highlight components of the sampling design that can be altered to improve statistical power.

Key Words.—amphibians; *Lithobates sylvaticus*; monitoring; power analysis; Wood Frog

INTRODUCTION

Over the last 20 years, increasing evidence of declines in amphibian populations has led to the development of many monitoring programs (e.g., the North American Amphibian Monitoring Program, NAAMP; Weir and Mossman 2005). Population monitoring is the repeated measurement over time of some attribute (i.e., state variable) that is informative of a population's status (Thompson et al. 1998; Noon 2003). For example, the Amphibian Research and Monitoring Initiative (ARMI) is using the proportion of sample units (e.g., ponds, stream stretches) occupied as an indicator of the status of amphibian populations in some national parks in the U.S. (Muths et al. 2005). In most cases, a primary objective of monitoring programs is to detect a declining trend in the state variable across time, so that action can be taken to prevent unacceptable losses or extinction (Thompson et al. 1998; Maxwell and Jennings 2005; Marsh and Trenham 2008).

In developing a population monitoring program, several important decisions are necessary. These decisions relate to a variety of issues from determining the goals of the program to selecting the analytical methods that will be used. Of all these decisions, however, selection of an appropriate state variable is among the most critical (Noon and McKelvey 2006). Given that a primary goal of most monitoring programs is to detect declines in the status of a population, the

state variable used in these programs should meet the following two criteria at a minimum: change in the variable should reflect declines in the population's status and change in the state variable should have a high probability of being detected (Gibbs 2000; Noon 2003; Maxwell and Jennings 2005; Noon and McKelvey 2006).

Counts of numbers of egg masses have been promoted as a valid state variable for monitoring Wood Frog (*Lithobates sylvaticus*) populations (Crouch and Paton 2000) and have been used to monitor Wood Frogs and other species of amphibians (Buckley and Beebe 2004; Vasconcelos and Calhoun 2006; Loman and Andersson 2007). In assessing the appropriateness of counts of numbers of egg masses for monitoring programs, some important issues have been considered (e.g., the cost of collecting the counts relative to collecting other kinds of data; Crouch and Paton 2000). However, time series of counts of the number of individuals in pond-breeding amphibian populations have other attributes that suggest they may be a poor state variable for monitoring programs. First, these time series tend to be highly variable (Green 2003). For example, coefficients of variation (CV) ranged from 0.29 to 1.29 across 10 time series of counts of Wood Frog adults from Berven (1990, 1995) and Vasconcelos and Calhoun (2006) (average = 0.71; CV is the standard deviation of a set of counts divided by the mean of the set of counts as in Lande et al. [2003] and Green [2003]). Similarly, time

Scherer and Tracey.—Power analysis for the use of counts of egg masses.

TABLE 1. The parameters used in the abundance, sampling and decision models, as well as the range of possible values for each parameter. The range of possible values for study duration and population growth rate is abbreviated in the table to minimize the length of the table. Study duration ranged from four to 30 years (in intervals of one year) and the population growth rate ranged from 0.90 (10% loss in egg mass abundance per year) to 1.0 (no change in egg mass abundance per year) in intervals of approximately 0.05%.

	Study Duration in number of years (27 levels)	Population growth rate (λ , 20 levels)	Detection Probability Per Surveyor (p , 3 levels)	Number of Surveyors (3 levels)	Type I Error Rate (α , 3 levels)
Possible Values	4	0.900	0.50	1	0.05
	5	0.905	0.75	2	0.10
	6	0.910	0.94	3	0.15
	⋮	⋮			
	30	1.00			

series of counts of the number of egg masses from a population of Dusky Gopher Frogs, *Rana sevosia*, and Natterjack Toads, *Bufo calamita*, showed high levels of variability (CV = 0.90 for Dusky Gopher Frogs [Richter et al. 2003] and CV \cong 0.51 for Natterjack Toads [Buckley and Beebee 2004]). Therefore, tests for a trend in these time series will have low power (i.e., a low probability of detecting a trend given a trend is present), unless the time series are of considerable length, the magnitude of their trends is large, or covariates are used to control for some of the variation (Reed and Blaustein 1995). For a population of Ornate Chorus Frogs (*Pseudacris ornata*), estimates of power indicated that a time series of 32 years would be required to achieve power of 0.80 (Hayes and Steidl 1997). Second, the use of counts in monitoring programs compromises inference regarding a trend in a state variable, because a trend may be confounded with variation in detection probability. Change in counts over time may represent change in actual abundance (the change of interest in monitoring programs) or change in the proportion of individuals in the population that are detected and counted (Williams et al. 2002; Grant et al. 2005).

The objective of this project was to assess the statistical power of using counts of the number of egg masses in monitoring programs for Wood Frogs. We addressed the following questions: How many years of count data will be required to have high power (power \geq 0.80) to detect negative trends of various magnitudes in the abundance of Wood Frog egg masses? How does variation in detection probability of Wood Frog egg masses and the number of surveyors conducting surveys affect the number of years required to achieve high power? What effect does increasing the Type I error rate, α , have on the number of years to achieve high power? We chose to base the simulations on Wood Frog egg masses, because sufficient data were available to parameterize a simulation model. Several time series of counts for Wood Frogs have been published (Berven 1990, 1995; Vasconcelos and Calhoun 2006), and detection probabilities of egg masses have been estimated (Grant et al. 2005; Scherer 2008). Because

time series from populations of other pond-breeding amphibians show similar levels of temporal variability (Green 2003), however, we suspect that the results of this analysis will provide useful guidance for monitoring other species as well.

METHODS

We used computer simulation to generate time series of counts of the number of Wood Frog egg masses similar to the kind of data that come from annual surveys at a breeding pond. The simulation model had three components: the abundance model, sampling model, and decision model. We used the abundance model to generate time series of egg mass abundance with a predetermined declining trend, and the sampling model to mimic the process of surveyors counting the number of egg masses at a pond. The sampling model assumed detection probability was less than one and, consequently, generated time series of counts that could be smaller than the number egg masses present at the pond. Finally, we used the decision model to analyze the trend of each simulated time series of egg mass counts and determine if the results of the analysis provided the correct inference regarding the predetermined decline in egg mass abundance.

Because we were interested in the effects of study duration (i.e., the number of years of monitoring), population growth rate, detection probability, number of surveyors, and Type I error rate on the power to detect trends, we generated 10,000 replicate time series each under a particular combination of model parameters (Table 1). For example, one set of 10,000 replicate time series was generated assuming a monitoring program of 10 years, a population growth rate of 0.95 (5% decline in abundance per year), a detection probability of 0.75, two surveyors, and α of 0.05.

Abundance model.—The purpose of the abundance model was to project egg mass abundance across years using different population growth rates (Table 1). To assess the effect of monitoring duration on statistical

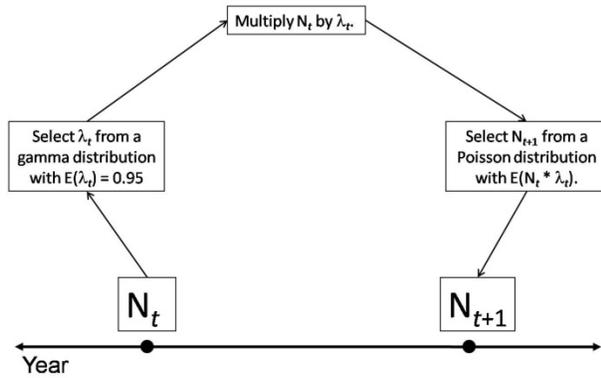


FIGURE 1. Schematic of the approach used to incorporate stochasticity into the time series of egg mass abundance. N_t and N_{t+1} represent egg mass abundance at years t and $t + 1$. λ_t represents the expected population growth rate between years t and $t + 1$ and, for the purposes of this figure, is set at 0.95 (5% decline per year). $E(\lambda_t)$ represents the expected value of the gamma distribution (i.e., the expected population growth rate). $E(N_t * \lambda_t)$ represents the expected value of the Poisson distribution.

power, we generated time series of egg mass abundance from four years to 30 years in duration (Table 1). The abundance model is a stochastic exponential model of the following general form:

$$N_{t+1} = \lambda_t N_t,$$

where N_t is the abundance of egg masses during the breeding season in year t and N_{t+1} is the abundance of egg masses the following breeding season. The population growth rate, λ_t , defines the proportional decline or increase in abundance between years t and $t + 1$. Values of λ_t less than one indicate a decreasing population, whereas values equal to or greater than one indicate a stable (no change in abundance) or increasing population (Gotelli 2001). For example, the abundance of egg masses will decline by 5% between the breeding seasons in years t and $t + 1$, if $\lambda_t = 0.95$. In a deterministic exponential model, the same value of λ_t would apply across every interval t to $t + 1$, and a plot of abundance across years would appear as a smooth curve. Time series of amphibian counts, however, are not smooth curves. Rather, they often show high levels of variability around a trend line (Pechmann et al. 1991; Richter et al. 2003; Loman and Andersson 2007). Therefore, we incorporated environmental and demographic stochasticity into the abundance model (Fig. 1). Environmental stochasticity is change in λ_t across intervals due to changes in environmental conditions (Gotelli 2001). During years of favorable environmental conditions, individuals have higher probabilities of survival and tend to produce more offspring. Consequently, abundance of egg masses increases between t and $t + 1$ ($\lambda_t > 1$). In years of poor conditions, reduced survival and reproductive rates cause a decrease in abundance of egg masses between t and $t + 1$ ($\lambda_t < 1$). We incorporated environmental stochasticity into the abundance model by randomly selecting λ_t from

a gamma distribution at every interval t to $t + 1$. We chose a gamma distribution because it is flexible and appropriate for modeling non-negative random variables (λ_t is always ≥ 0 ; Rice 1995). The expected value of the gamma distribution was the population growth rate of interest for the current set of replicate time series. For example, the expected value of the gamma distribution from which each λ_t was drawn was 0.95 for all simulated time series with a population growth rate = 0.95. To implement demographic stochasticity into the abundance model, we multiplied abundance of the previous year, N_t , by the selected value of λ_t , and the resulting product became the expected value of a Poisson distribution. We drew the abundance value for N_{t+1} from this Poisson distribution (Allen 2003; Fig. 1).

For each simulation, the initial population size, N_0 , was 500 egg masses which was in the range of counts of adult female Wood Frogs (Berven 1995) and Wood Frog egg masses (Egan and Paton 2004) from field studies. To examine the effect of population growth rate on the power to detect a trend, we projected egg mass abundance with an expected value of λ_t as low as 0.9 (i.e., a 10% annual decline in abundance) to as high as one (i.e., no change in abundance across years; Table 1) with 18 increments in between. Reported rates of decline in published analyses of amphibian time series ranged from 0.004% to 8% per year (Hayes and Steidl 1997; Meyer et al. 1998).

Sampling model.—The abundance model projected the number of egg masses for every breeding season, t , in each simulated time series. We developed the sampling model to simulate the process of one to three surveyors independently searching the entire pond and counting egg masses. Because some proportion of Wood Frog egg masses are not detected during many surveys, a count will represent a fraction of the total number of egg masses in the pond (Grant et al. 2005; Scherer 2008).

We used the binomial model to simulate the sampling process. The binomial model can be used to simulate the number of successful outcomes given a particular number of trials and a probability of success. In this project, we used the binomial model to select randomly the number of egg masses that were detected and counted during a breeding season, C_t , given the total number of egg masses at the pond, N_t (from the abundance model), and a probability of detection by a surveyor, p . Previous studies suggest the probability of detection of Wood Frog egg masses varies between years and surveyors (Grant et al. 2005; Scherer 2008). Therefore, we randomly selected the probability of detection for each breeding season and surveyor from a beta distribution. The beta distribution is often used to model probabilities because, like a probability, it is defined on the interval from 0 to 1. To evaluate the

effect of detection probability on power, we created three beta distributions with expected values that represented scenarios of high ($p = 0.94$), medium ($p = 0.75$) and low ($p = 0.50$) detection probability. The detection probability of Wood Frog egg masses is generally high, because they are large (approximately 8 cm diameter) and tend to be deposited at or just below the surface of the water (Hammerson 1999; Grant et al. 2005). For the high detectability scenario, we estimated the beta distribution by calculating the mean and variance of 37 estimates of p from two field studies of Wood Frog egg masses (Grant et al. 2005; Scherer 2008) using a method-of-moments approach (Rice 1995). The expected value of p was 0.94 (variance, $\sigma_p^2 = 0.0064$). For the medium and low detectability scenario, we used the same variance as in the high detectability scenario but changed the expected values of p to 0.75 and 0.50.

In simulations where two or three people survey a pond, we assumed each surveyor conducted an independent search of the entire pond. Therefore, each egg mass had multiple opportunities to be detected, and the probability of detection had a slightly different interpretation. In those simulations, p represented the probability that an egg mass was detected and counted by at least one of the surveyors. The probability that two surveyors fail to detect and count an egg mass can be represented as: $(1 - p_1) * (1 - p_2)$, where p_1 and p_2 represent the detection probabilities for each surveyor and were independently drawn from a beta distribution. Therefore, the probability that an egg mass was detected and counted by at least one of the surveyors is $[1 - ((1 - p_1) * (1 - p_2))]$. We denoted this quantity as p^{*2} and used it as the probability of detection in the binomial model. Similarly, in simulations with three surveyors, the probability that at an egg mass was detected and counted by at least one of the surveyors is $[1 - ((1 - p_1) * (1 - p_2) * (1 - p_3))]$ and was denoted as p^{*3} .

Decision model.—We used the decision model to determine if a declining trend in the time series of egg mass counts was present. For each time series, we log-transformed the counts and used linear regression (LR) to evaluate the null hypothesis of no trend (as in Meyer et al. 1998). An essential step in null hypothesis testing is to specify an acceptable Type I error rate (α ; the probability of falsely rejecting the null hypothesis), and it is common in ecological studies to set α at 0.05 (Di Stefano 2003). Yet, the indiscriminant use of $\alpha = 0.05$ does not take the relative costs of a Type I and Type II (failing to reject a false null hypothesis) errors into consideration. For management of wildlife populations, a Type II error may be more costly than a Type I error (Field et al. 2007). Failing to take action early in the decline of a population may result in more costly management actions (e.g., captive rearing programs) or irreversible losses in populations. Therefore, many

authors have argued that increasing α is appropriate in order to increase power in monitoring programs (Gibbs et al. 1998; Field et al. 2007). To evaluate the effect of increasing α on the power to detect trends in time series of egg mass counts, we used $\alpha = 0.05, 0.10$ and 0.15 .

We used the following rules to determine if the sampling methods and LR resulted in the correct inference regarding the underlying trend in egg mass abundance. For simulations with a population growth rate < 1.0 , the results of the LR gave the correct inference if the P -value $\leq \alpha$ and the estimated slope of the regression line ($\hat{\beta}_1$) was < 0 (i.e., the expected negative trend was detected). For simulations with a population growth rate = 1.0, the results of the LR provided the correct inference if the P -value $> \alpha$, or if the P -value $< \alpha$ and the estimated slope of the regression line was > 0 (i.e., a negative trend was not detected). We conducted simulations in the R statistical software package (R Core Development Team 2007) and used the proportion of time series that resulted in a correct inference as a measure of statistical power.

Assessing temporal variability in simulated data.—A key factor in the power of detecting a trend is the amount of temporal variability in a time series (Gibbs 2000). Therefore, it is important that the variability in the simulated time series was comparable to the variability reported from field studies of Wood Frog populations. Berven (1995) provided time series of counts of Wood Frog females from 10 populations in Michigan, Maryland, and Virginia. The duration of the time series ranged from six to 14 years, and we computed the CV for each time series as an estimate of the variability in numbers of Wood Frog egg masses across years. We compared the variability in the simulated time series of egg mass counts to the variability in the time series of females from Berven (1995) both graphically and numerically.

For the graphical analysis, we extracted and graphed the counts that represented the 2.5th and 97.5th percentile and the 25th and 75th percentile for each year from a simulated set of 40,000, 14-year time series. We compared this graph to the 14-year time series from Berven (1995; Fig. 2). To make this comparison meaningful, we estimated the trend in the time series of Wood Frog females from Berven (1995) by fitting an exponential model to the data and used the estimate as the decline rate in the simulated time series. In addition to the graphical comparison, we compared the distribution of CVs from the simulated time series with the CVs of the 10 time series from Berven (1995).

RESULTS

Graphically, variability in the simulated time series of the numbers of egg masses approximated variation in the time series of counts of female Wood Frogs from the

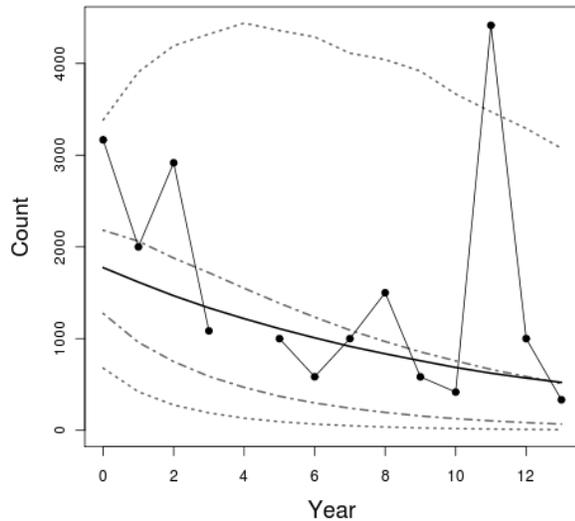


FIGURE 2. A comparison of the variability in the simulated time series of egg mass counts to the variability in a time series of counts of females from a population of Wood Frogs in Michigan (Berven 1995). The black circles connected by a solid line represent the time series of counts of females from this population (the count from the fourth year was missing). The dotted line represents the 2.5th and 97.5th percentiles, the dashed line represents the 25th and 75th percentiles, and the bolded solid line represents the mean of the 40,000 simulated time series.

field study (Fig. 2). Of the 13 counts from Berven (1995), 12 (92%) are within the middle 95% of counts from the simulation model. Eight of the 13 (62%) are within the middle 50% of counts from the simulation model. Numerically, the simulated time series also showed similar levels of variability as the time series from the field studies. The mean CV across the 40,000 simulated time series was 0.80, and the middle 50% of CVs ranged from 0.53 to 1.02. The CV of the 14-year time series of counts of Wood Frog females from Berven (1995) was 0.81. The average CV from the other nine Wood Frog populations in Berven (1995) was 0.85 (range = 0.29 to 1.59), similar to the average CV across the simulated time series.

Under the poorest conditions for detecting a decline in the simulated time series of annual counts of egg masses ($p = 0.50$, one surveyor and $\alpha = 0.05$), more than 30 years were required to attain high power for detecting a decline when the population growth rate was near 1.0 (Fig. 3a). As expected, power increased as the duration of the study increased and the population growth rate decreased (Fig. 3). Even at the smallest population growth rate (expected value of $\lambda_r = 0.90$), however, 12 years of counts were required to achieve power of 0.80 under these conditions (Fig. 3a). After 12 years with a population growth rate of 0.90, the number of egg masses in the population would have declined by more than 70% from the starting value of 500 egg masses.

Previous research suggests the detection probability of Wood Frog egg masses is much higher than 0.50 (Grant et al. 2005; Scherer 2008). Improved detection

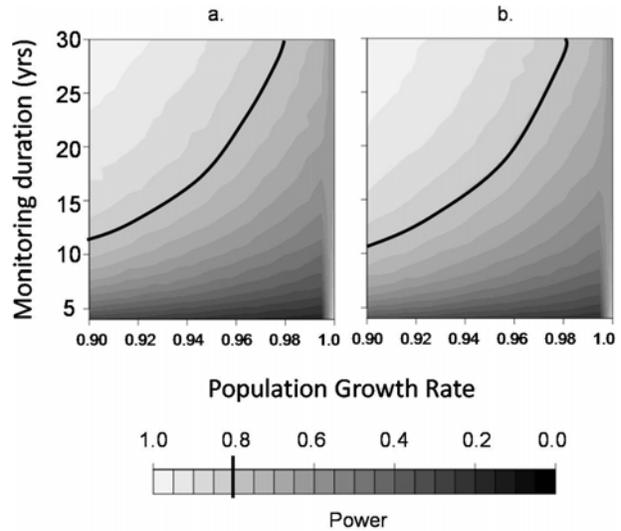


FIGURE 3. Power to detect negative trends in egg mass counts for different monitoring durations and population growth rates (λ) and under two combinations of detection probability and number of surveyors: a) detection probability, $p = 0.5$ (low detectability), one observer; b) $p = 0.94$ (high detectability) and three observers. As the shading changes from light gray to black in each graph, power decreases. The thick black line represents power of 0.80, and all area above and to the left of the line represents monitoring conditions of high power. The far right-hand side of each graph represents simulations with an expected population growth rate, $\lambda = 1.0$ (no underlying trend in egg mass counts). In these simulations, a correct inference resulted when the regression was not significant. As with the simulations with $\lambda < 1.0$, lighter shading indicates that a higher percentage of simulations resulted in a correct inference. As the number of years of monitoring increases, the shading gets darker, because a higher percentage of simulations result in a significant regression (i.e., an incorrect inference or higher Type I error rates). In both graphs, $\alpha = 0.05$.

probability, whether by improving the ability of surveyors to find egg masses or adding surveyors to field crews, resulted in only slight improvements in power (Fig. 3a and 3b). Increasing detection probability and the number of surveyors from their minimum values ($p = 0.5$ and 1 observer) to their maximum values ($p = 0.94$ and 3 observers) only decreased the amount of time required to achieve high power by one to two years for a particular population growth rate (Fig. 3a and 3b). Even under the best sampling conditions ($p = 0.94$ and 3 observers), time series of two decades or more were still required to achieve high power when population growth rates were near one (approximately 0.96 to 0.99, Fig. 3b), and a minimum of a decade of counts was required when population growth rates were near 0.90.

Increasing α from 0.05 to 0.10 decreased the number of years required to achieve high power by 1 to 3 years across population growth rates and sampling conditions (Fig. 4), and increasing α from 0.05 to 0.15 resulted in a decrease of 2 to 4 years. By definition, however, increasing α has a cost of higher Type I error rates. The results of the simulations highlight this cost. As α increased, significant declining trends were detected in 1

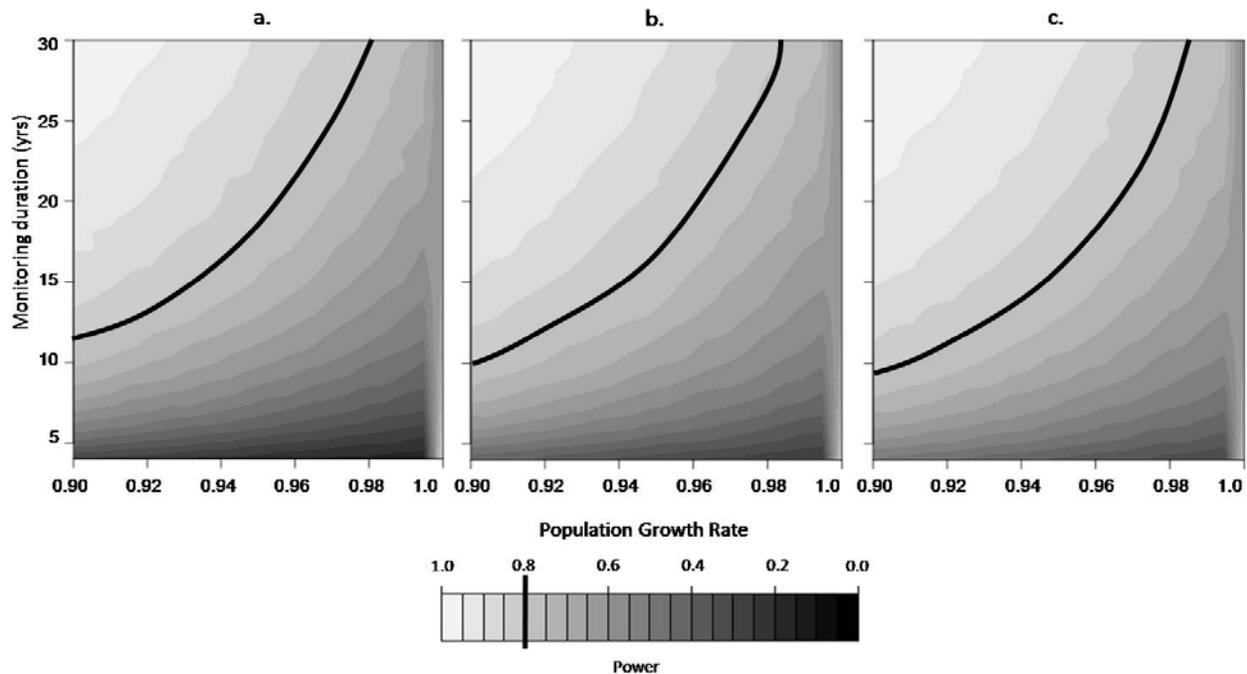


FIGURE 4. Power to detect negative trends in egg mass counts for different levels of α : a) 0.05, b) 0.10, and c) 0.15. As the shading changes from light gray to black on each plot, power decreases. The thick black line represents power of 0.80, and the area above and to the left of the black line represents monitoring conditions of high power. The far right-hand side of each graph represents simulations with an expected population growth rate, $\lambda = 1.0$ (no underlying trend in egg mass counts). In these simulations, a correct inference resulted when the regression was not significant. As with the simulations with $\lambda < 1.0$, lighter shading indicates that a higher percentage of simulations resulted in a correct inference. Because α establishes the Type I error rate, the shading is darker for a given monitoring duration across the three graphs. For all levels of α , this figure shows simulated power for $p = 0.50$ and one observer.

to 11% more of the simulations with a population growth rate = 1.0 (Fig. 4 and 5). Noting the high rate of Type I errors in time series of 14 years or more is also important. Across simulations, the probability of a Type I error ranged from 0.34 to 0.44 for time series with 14 years or more of counts.

DISCUSSION

A common reason for failure in monitoring programs is insufficient duration of financial and institutional support for collection of data (Elzinga et al. 2001; Field et al. 2007). A power analysis should be a central component in the evaluation of a proposed monitoring program's survey design and state variable (Gibbs 2000; Maxwell and Jennings 2005; Legg and Nagy 2006; Field et al. 2007) and can provide valuable insights regarding the necessary duration of the project and other elements of the sampling design that can be altered to improve efficiency.

The results of this power analysis indicate that a minimum of nine years of monitoring will be required to achieve high power to detect declining trends in counts of Wood Frog egg masses unless rates of decline are greater than 10% per year. At lower rates of decline,

two decades or more of counts may be necessary to achieve high power. Without a long-term commitment, therefore, initiation of a monitoring program for a Wood Frog population with egg mass counts as the state variable will likely represent an inefficient use of resources. In addition, the results suggest that improving the ability of surveyors to find egg masses (e.g., via better training) or increasing search effort would only marginally increase power for a given duration and population growth rate. Reductions in power due to the use of counts were small compared to the reductions caused by the high levels of variability observed in time series from Wood Frog populations (Berven 1990, 1995; Vasconcelos and Calhoun 2006).

Increasing α , on the other hand, resulted in larger increases in power. Over the range of values used in these simulations, increases in α from 0.05 to 0.10 reduced the number of years to achieve high power by one to three years, while increases from 0.05 to 0.15 resulted in a reduction of two to four years. Of course, these improvements in power were accompanied by higher Type I error rates. Field et al. (2004) argued that the cost of Type I errors (concluding that a population is declining when it is not) in monitoring programs are often smaller in magnitude and duration than Type II

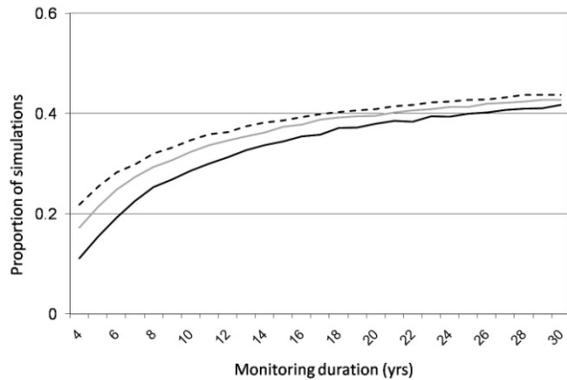


FIGURE 5. For different monitoring durations and levels of α , the proportion of simulations in which a significant declining trend was detected even though the population growth rate = 1.0 (solid black line, $\alpha = 0.05$; solid gray line, $\alpha = 0.10$; dashed black line, $\alpha = 0.15$).

errors (failing to conclude that a population is declining when it is) and setting α at the conventional level of 0.05 fails to account for these differential costs. Further, they propose a decision-theoretic framework for finding an appropriate balance between Type I and II error rates. Generally, as the economic value of a species increases relative to the cost of initiating management action in response to detecting a decline, the optimal value of α increases (Field et al. 2004).

Noting that the simulations used in this study may overestimate the number of years required to achieve power of 0.80 is important. Unless a complete count of the number of individuals in a population each year is achieved, the variability in a time series of abundance is comprised of two sources: variation in actual abundance over the time series (i.e., process variation) and variation due to the fact that abundance is estimated from a sample (i.e., sampling variation; Link and Nichols 1994). Therefore, sampling variation increases the total variation in a time series and, consequently, reduces the power to detect a trend. Though this step is rarely completed in monitoring studies, sampling variation should be removed from a time series prior to conducting a trend analysis (Barker and Sauer 1992; Link and Nichols 1994). We did not remove sampling variation from the simulated time series in this study; therefore, estimates of power may be biased low. However, we simulated the sampling of egg masses under low and high detectability scenarios. Under the highest detectability scenario (three observers and probability of detection of 0.94), a complete census of egg masses would be achieved in most years and sampling variation would be low. Estimates of power from these simulations are nearly identical to estimates from the low detectability scenarios, which suggests the presence of sampling variation in the simulated time series did not result in an overestimate of the number of years required to achieve high power.

Although the conclusions in this study are based on

simulations using counts of numbers of Wood Frog egg masses, the temporal variability in time series across many populations suggests the results may apply to other amphibian species and counts of other life-history stages (e.g., juveniles and adults). Green (2003) calculated CVs for over 500 time series from populations of pond-breeding amphibians and reported a mean CV of 0.75 (SE = 0.037). This value is similar to the mean CV from the 10 populations of Wood Frogs studied by Berven (1995) and to the levels of variability used in the simulations for this study. Monitoring populations of amphibians with lower levels of temporal variability (e.g., stream-breeding species and terrestrial direct-developing species; Green 2003), however, may require fewer numbers of years to achieve high power.

The results of our simulations and other power analyses (Reed and Blaustein 1995; Hayes and Steidl 1997) indicate that the use of counts in amphibian monitoring programs may suffer from low statistical power. Though we didn't address the issue in this study, using counts will also compromise inference, because trends in counts are often confounded with variation in detection probability (Nichols 1992; Williams et al. 2002). Therefore, the use of counts in herpetological field studies has been highly criticized, and researchers and managers have been encouraged to consider state variables for which analytical methods that account for detection probability are available (Pollock et al. 2002; Mazerolle et al. 2007). Advances in the modeling of data common in amphibian monitoring programs (e.g., presence-absence data, call survey data, capture-recapture data) have expanded the range of state variables for which estimates that account for detection probability can be derived. Though the models are too numerous for a thorough treatment here, we provide a few examples with associated references and refer readers to a recent review of methods for estimating demographic parameters from herpetological field data by Mazerolle et al. (2007).

For managers monitoring amphibian populations over small spatial scales (e.g., populations at a single wetland), abundance is often the preferred state variable. Based on the temporal variability observed in counts, however, abundance in many amphibian populations is also likely to be highly variable. Therefore, other demographic parameters may be more appropriate. In long-lived amphibians, annual survival probability of adults tends to be high and shows low temporal variation (Scherer et al. 2008; Bell and Pledger 2010). Life-history theory predicts that population growth rate, λ , of these species will be most sensitive to changes in adult survival probability, and many studies of species from various taxonomic groups, including amphibians, have reported support for this prediction (Biek et al. 2002; Pfister 1998; Sæther and Bakke 2000). Consequently, survival probability of adults may be an appropriate state

variable for monitoring populations of long-lived amphibians. While capture-recapture models for estimating survival probability have been in use for many years, advances in capture-recapture modeling account for common sources of bias in estimates of survival probability and expand the range of other demographic parameters that can be estimated. For example, models for capture-recapture data collected under the robust design account for temporary emigration, a potential source of bias in estimates of survival probabilities, and provide estimates of many other demographic parameters, e.g., abundance and population growth rate (Kendall et al. 1997; Kendall and Bjorkland 2001).

Managers monitoring amphibian populations over broad spatial scales (i.e., regional populations) also have a broad range of state variables from which to choose. The models of MacKenzie et al. (2006) can be used with data from repeat presence-absence surveys at wetlands to estimate the proportion of wetlands that are occupied by a species (i.e., occupancy) and model the processes that lead to change in occupancy across time (i.e., extinction and colonization). Since its development, the original occupancy model of MacKenzie et al. (2002) has been extended to accommodate a variety of sampling challenges (e.g., heterogeneity in detection probability induced by variation in abundance; Royle and Nichols 2003) and to estimate other state variables of interest (e.g., community-level occupancy; MacKenzie et al. 2006). Models for call survey data collected from regional populations have also been developed. For example, the model of Royle and Link (2005) uses call survey data to derive an index of the distribution of abundances across wetlands.

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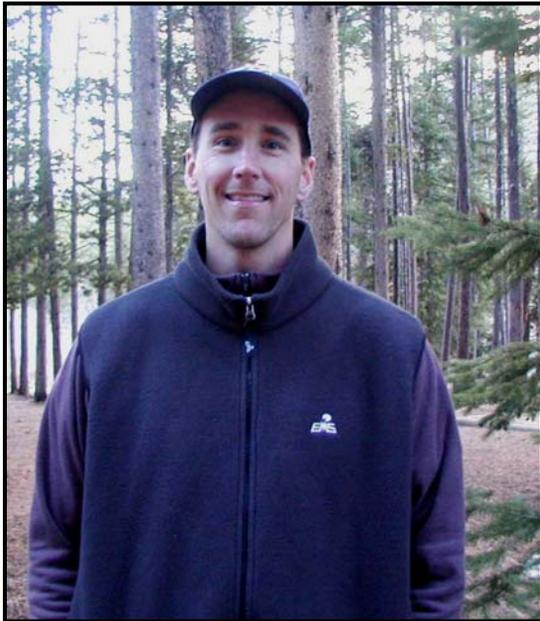
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