

Minimum Time Required to Detect Population Trends: The Need for Long-Term Monitoring Programs

EASTON R. WHITE 

Long-term time series are necessary to better understand population dynamics, assess species' conservation status, and make management decisions. However, population data are often expensive, requiring a lot of time and resources. What is the minimum population time series length required to detect significant trends in abundance? I first present an overview of the theory and past work that has tried to address this question. As a test of these approaches, I then examine 822 populations of vertebrate species. I show that 72% of time series required at least 10 years of continuous monitoring in order to achieve a high level of statistical power. However, the large variability between populations casts doubt on commonly used simple rules of thumb, such as those employed by the IUCN Red List. I argue that statistical power needs to be considered more often in monitoring programs. Short time series are likely underpowered and potentially misleading.

Keywords: ecological time series, experimental design, population monitoring, statistical power, sampling design

Observational studies and population time series have become a cornerstone of modern ecological research and conservation biology (Magurran et al. 2010, Peters 2010, Hughes et al. 2017). Long-term data are necessary to both understand population dynamics and to assess species extinction risk. Some time series may now be considered long-term (e.g., continuous plankton recorder; Giron-Nava et al. 2017), but most are still short. Time series are typically short because of short funding cycles and typical experimental time frames (Field et al. 2007, Hughes et al. 2017).

How long of a time series is actually necessary? This question has important implications for both research and management (Nichols and Williams 2006). A short time series may lead to wrong conclusions, given large natural year-to-year variability (McCain et al. 2016). Managers need to know when action is needed for a population. Therefore, managers must understand when a population trend over time is actually meaningful. In addition, sampling is typically expensive; therefore, we also do not want to sample for longer than is necessary. For example, Gerber and colleagues (1999) investigated the minimum time series required to estimate population growth of the endangered but recovering eastern North Pacific gray whale (*Eschrichtius robustus*). They used a long-term census to retroactively determine the minimum time series required to assess threat status. They found that only 11 years were needed, 8 years before

the delisting decision was made. This highlights the importance of estimating the minimum time series required as an earlier decision would have saved time and money (Gerber et al. 1999). Furthermore, waiting too long to decide an action can imperil a species for which management action could have been taken earlier (Martin et al. 2012, 2017). Specific guidelines are therefore needed to determine when a time series is adequate. For example, the International Union for Conservation of Nature (IUCN) Red List Categories and Criteria suggest, under criterion A2, a species qualifies as vulnerable if it has experienced a 30% decline over 10 years, or three generations (IUCN 2012).

In past work, questions related to the minimum time series required to estimate trends in population size over time have been investigated (Wagner et al. 2009, Giron-Nava et al. 2017). For example, Rhodes and Jonzen (2011) examined the optimal allocation of effort between spatial and temporal replicates. Using simple populations models, they found that the allocation of effort depends on environmental variation, spatial and temporal autocorrelation, and observer error. Rueda-Cediel and colleagues (2015) also used a modeling approach but parameterized a model specific for a threatened snail, *Tasmaphena lamproides*. They found that for this short-lived organism, 15 years was adequate to assess long-term trends in abundance. However, these studies and other past work have typically only addressed theoretical aspects of monitoring design or have been focused on a few species.

Statistical power is not a new tool (Cohen 1992, Thomas 1997, Thomas and Krebs 1997, Gibbs et al. 1998), but it is still underappreciated in ecological research (Legg and Nagy 2006). Therefore, I begin by reviewing key concepts of power analyses in relation to time series analysis. I then explain how simulation approaches have been used to estimate the minimum time required to estimate long-term population trends. Finally, I take an empirical approach to estimate the minimum time required for 822 animal populations.

Statistical power in time series analyses

An important step in experimental design is to determine the number of samples required. For any particular experiment, four quantities are intricately linked: significance level (α), statistical power, effect size, and sample size (Legg and Nagy 2006). The exact relationships among these quantities depends on the specific statistical test. A type I error is a false positive, an incorrect rejection of a true null hypothesis. For example, if a time series was assessed as significantly increasing or decreasing—when there was no true significant trend—this would be a false positive. The significance level (α , the probability of a false positive) is often set at .05 (although this is purely historical; Mapstone 1995). A type II error (β) is a failure to detect a true trend or a failure to reject a false null hypothesis. Statistical power is $1 - \beta$. Informally, statistical power is the probability of detecting a trend if it actually exists. The effect size is an estimate of the strength of a particular phenomenon.

Prior to an experiment, one could set appropriate levels of power and significance level and the effect size to estimate the sample size required for the experiment. This approach, however, is not straightforward for a time series or more complicated scenarios (Johnson et al. 2015), because the data are clearly not independent.

In the context of time series data, sample size can be the number of study sites surveyed, the frequency of surveys per year, and the number of years surveyed. For example, Gibbs and colleagues (1998) examined how many times within a year a population needs to be sampled in order to ensure high statistical power. They found that the sampling intensity within a year differed greatly depending on the species, because of differences in population variability. I use a similar approach but, instead, focus on the number of years required to estimate trends in abundance. In line with Gibbs and colleagues (1998), I would expect these results to be strongly dependent on population variability. Unlike Gibbs and colleagues (1998), I do not lump species together and, instead, study the differences between and within species.

Simulation approach

One approach to determining the minimum time series length needed is through repetitive simulations of a population model (Gerrodette 1987, Gibbs et al. 1998). This is the same approach one might use in sample size calculations for any experimental design too complicated for simple power analyses (Bolker 2008, Johnson et al. 2015). Essentially, a

population model, with a selected set of parameter values, is simulated repetitively for a number of years. As an example, we can take the following population model for population size N at time t :

$$N(t + 1) = N(t) + r(t) + \varepsilon, \text{ with } \varepsilon \sim N(\mu, \sigma) \quad (1)$$

where ε is a normally distributed random noise term with mean μ and standard deviation σ . The rate of growth (r) is the trend strength of the increase or decrease (i.e., the estimated slope from linear regression). Although there are many approaches to studying populations trends (Thomas 1996), linear regression is the simplest and most commonly applied.

With regard to detecting time series trends, statistical power is the proportion of simulations in which the slope parameter from linear regression is significant at the .05 threshold. A statistical power of .8 would indicate that, if there was a true trend in abundance, there would be a .8 probability of detecting the trend. Values of .05 for the significance level and .8 statistical power are purely historical (Cohen 1992). Therefore, it is important to also examine the effect of changing these values (supplemental figure A4). Predictably, as the significance level decreases or the power required increases, more years of sampling are required (figure A4).

I set the significance level at .05 and then simulated the model in equation 1 (figure 1a). Statistical power increases with increases in the length of time sampled (figure 1b). Where power is greater than .8 (the dashed line), that is the minimum time required (T_{\min}) to be confident in the detection of a long-term trend in abundance. As was shown previously (Rhodes and Jonzen 2011, Rueda-Cediel et al. 2015), statistical power increases with larger trend strength and lower population variability (figure 1c and d). Simulation approaches can be useful before designing a monitoring program or when a realistic model exists for the population in question.

Any population model could be used in this approach (e.g., see supplemental figures A6, A7). Ideally, the specific model choice should be tailored to the population of interest. As an example, I determined the minimum time required to estimate long-term population trends using a stochastic, age-structured model of lemon shark population dynamics in the Bahamas (White et al. 2014). I found that over 27 years of continuous monitoring were needed in this particular scenario (supplemental figure A7). Not surprisingly, the minimum time required for the lemon shark population was strongly dependent on model parameters (see figure A7). Similarly, Rueda-Cediel and colleagues (2015) used a matrix model parameterized for a particular snail species. They used the model to argue that only 10–15 years were needed to accurately assess trends in abundance.

Empirical approach

As an empirical test of these ideas, I used a database of 2444 population time series compiled by Keith and colleagues

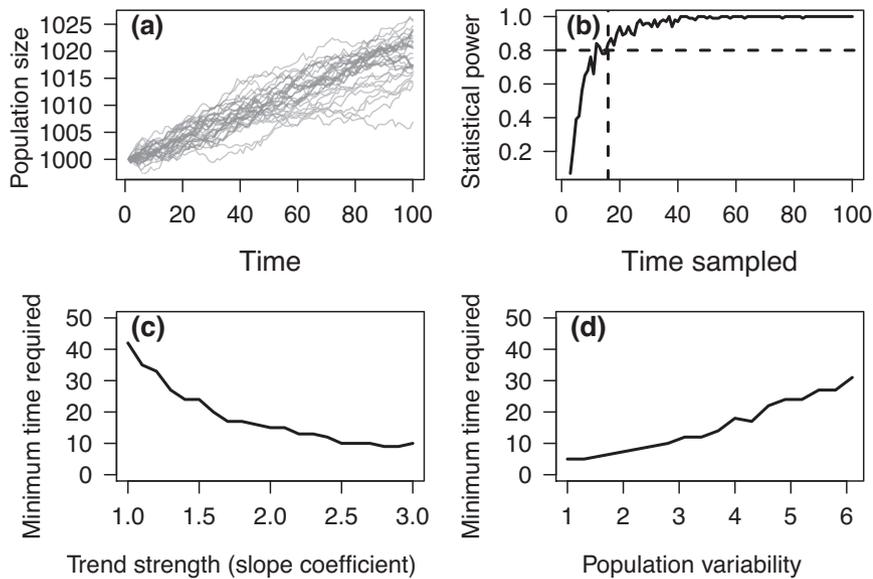


Figure 1. (a) Example of a simulated time series for 40 replicates. (b) Statistical power versus the simulated time series length. The horizontal, dashed line is the desired statistical power of .8. The vertical, dashed line is the minimum time required to achieve the desired statistical power. (c) Minimum time required (T_{\min}) for simulations with different values of the trend strength (r) and $\sigma = 5.0$. (d) Minimum time required for different levels of population variability σ and $r = 1.5$. In each case, the minimum time required is the minimum number of years to achieve .8 statistical power given a significance level of .05.

(2015). The data are originally from the Global Population Dynamics Database (NERC Centre for Population Biology Imperial College 2010) and several other sources (Keith et al. 2015). I filtered out short time series (less than 35 years), and those with missing data, leaving 822 time series. The data includes information on 477 vertebrate species of birds ($n = 747$), mammals ($n = 7$), sharks ($n = 2$), and bony fish ($n = 66$).

I assumed that each time series was long enough to include all necessary information (e.g., variability) about the population. In other words, each time series was a representative sample. I then performed a type of retrospective power analysis—termed *retrospective* because the data has already been collected (Thomas 1997). I first took all possible contiguous subsamples of each time series. For example, a time series of 35 years had 34 possible contiguous subsamples of length 2, 34 possible contiguous subsamples of length 3, and continuing until 1 possible contiguous subsample of length 35 (Gerber et al. 1999, Brashares and Sam 2005, Giron-Nava et al. 2017). The subsampling avoids some of the common pitfalls of retrospective power analyses (Thomas 1997, Thomas and Krebs 1997). In line with the simulation approach, I determined the proportion of subsamples of a particular length that had estimated slope coefficients statistically different from zero. This proportion is a measure of statistical power. Finally, I determined which subsample length is required to achieve a certain threshold of statistical

power (.8; Cohen 1992). The minimum subsampled length that met these criteria was the minimum time series length required (T_{\min}). All analyses were conducted in R (R Core Team 2017).

Estimates of the minimum time required

Across all the populations, I found an average minimum time series length required (T_{\min}) of 15.9 (standard deviation = 8.3), with a wide distribution (figure 2b). Approximately, 72% of the populations required at least 10 years of monitoring. Estimates of T_{\min} varied between biological class (figure 2a). Ray-finned fish (class Actinopterygii) typically had estimates of T_{\min} over 20 years. Birds (class Aves) had a much wider distribution of T_{\min} , but usually required fewer years of sampling. The wider distribution is probably due in part to the larger number of Aves samples compared with other classes. Differences between these classes can be partly explained by differences in variability in population size and strength of trends in abundance (supplemental figure A3).

This time frame is in line with past work on a short-lived snail species (Rueda-Cediel et al. 2015) and a long-lived whale species (Gerber et al. 1999). Hatch (2003) used seabird monitoring data to estimate minimum sampling requirements. He found that the time required ranged from 11 to 69 years, depending on species, trend strength, and study design. All of this past work has been limited to a small number of species. This article is the first attempt to document the minimum sampling requirements for such a wide diversity and number of species.

Correlates for minimum time required

The minimum time series length required was strongly correlated with trend strength (i.e., the estimated slope coefficient from linear regression), coefficient of variation in population size, and autocorrelation in population size (figure 3a–c). All three of these explanatory variables were significant and had large effect sizes (see supplemental table A1). Combined, trend strength, coefficient of variation in population, and autocorrelation account for 75.1% of the explained deviance (Zuur et al. 2009) in minimum time series length required. Therefore, by knowing these three aspects of a time series, a reasonable estimate for the minimum time series length required can be made.

There was life-history information available (Myhrvold et al. 2015) for 547 populations representing 315 different species, all of which were birds (Aves class). Some life-history traits were significant predictors for the minimum

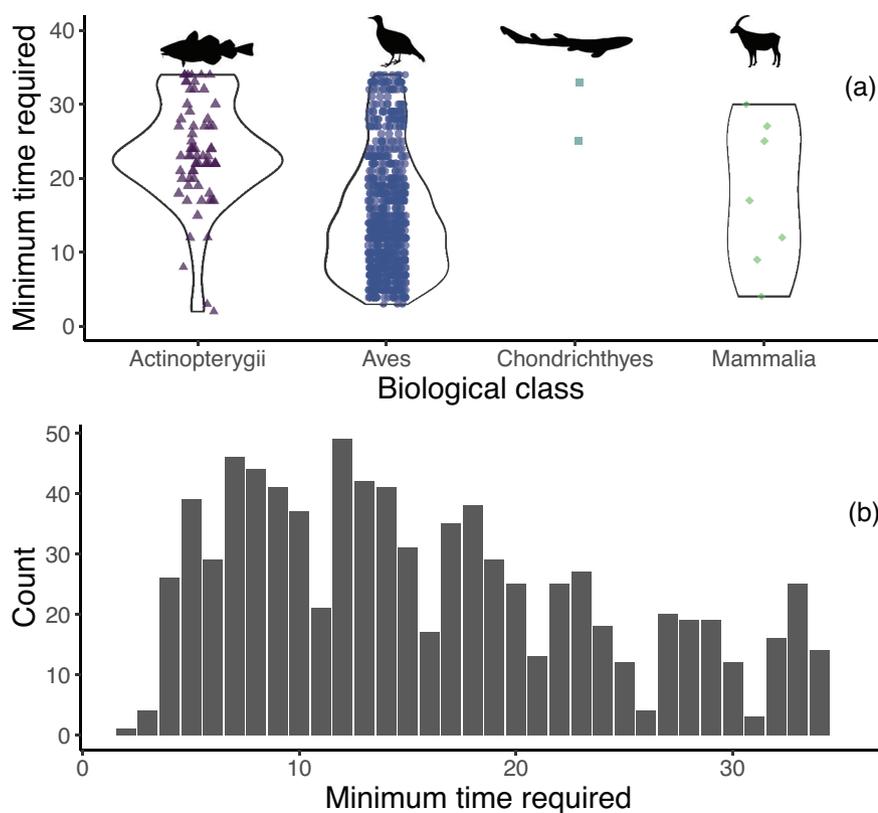


Figure 2. (a) Distributions of the minimum time required for populations from four different biological classes. (b) Distribution of minimum time required for all populations regardless of biological class. The minimum time required calculation corresponds to a significance level of .05 and statistical power of .8.

time required (figure 3d–h; supplemental tables A2 and A3). However, even combined, all five of the life-history traits accounted for only 5.99% of the explained deviance in minimum time series length required. In addition, when accounting for trend strength, coefficient of variation, and autocorrelation, no life-history traits were significant predictors of the minimum time required (table A3). Because of the shared evolutionary history of populations and species, this lack of independence may affect regression results (Felsenstein 2008). I used the APE package (Paradis et al. 2004) in R to run phylogenetically corrected regressions within the Aves class. The overall results were not altered when accounting for phylogeny (supplemental figure A10).

I initially hypothesized that species with longer lifespans or generation times might require a longer sampling period. This result could have been caused by at least two factors. First, the data I used might not have included a diverse enough set of species with different life-history traits. Second, the question I posed, whether a population is increasing or decreasing, was specifically concerned with population trends over time. Therefore, life-history characteristics may be more important for other questions more closely tied to species biology. For example, Blanchard and colleagues (2007) used detailed simulations of spatially

distributed fisheries to compare survey designs. They found that statistical power depended on temperature preferences and the degree of population patchiness, presumably because the survey designs included a spatial component.

Evaluating the IUCN criteria

I examined a subset of populations with observed declines of 30% or greater over 10 years, qualifying all of them as vulnerable under IUCN criterion A2 (IUCN 2012). This resulted in 162 populations. I then compared the minimum time required to achieve .8 statistical power (T_{\min}) to the minimum time required under the IUCN criteria (figure 4). For populations below the identity line in figure 4, IUCN criteria would require more sampling compared to estimates for T_{\min} . Furthermore, populations above the identity line are cases in which the IUCN criteria would classify a population as vulnerable despite not having sampled enough years to achieve high statistical power (figure 4). The silhouettes on figure 4 highlight that species with long generation times had larger discrepancies between T_{\min} and the

minimum time required for IUCN assessments (supplemental figure A5).

For the populations I examined, the IUCN criteria may be overly simplistic (figure 4). For many populations, the IUCN criteria suggest that more years than necessary are required to assess a population as vulnerable. Conversely, for other populations, the IUCN criteria suggest sampling times that are less than the minimum time required for statistical power. This suggests that the IUCN criteria are probably too simplistic, because the minimum time required does not correlate with generation time or other biological covariates (figure 3d–h). Instead, assessments of long-term trends could rely on one of two approaches. First, a specific model could be built and simulated for the species of interest. An estimate of the minimum number of years for a particular threshold of statistical power could then be determined (e.g., see supplemental figure A7). Alternatively, if one had estimates of the population trend, the population variability, and the autocorrelation, it would then be possible to estimate the minimum number of years required using the regression model provided in table A1.

Related questions

Keith and colleagues (2015) studied the same data set to determine how predictive a current population trend was of

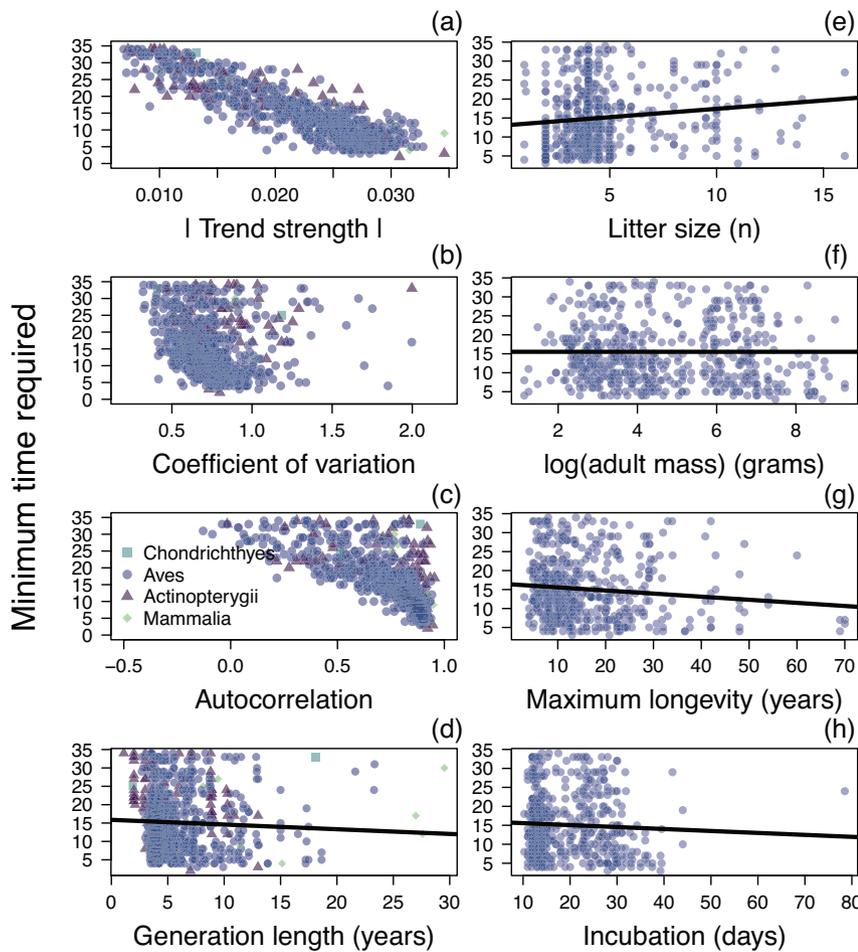


Figure 3. Minimum time required to estimate change in abundance correlated with (a) trend strength (absolute value of slope coefficient estimated from linear regression), (b) coefficient of variation in interannual population size, (c) temporal lag-1 autocorrelation, (d) generation length (years), (e) litter size (n), (f) log adult body mass (grams), (g) maximum longevity (years), and (h) incubation (days). The lines in each plot represent the best fit line from linear regression.

future trends. They showed that, for many species (except birds), past declines were actually more predictive of subsequent increases. This shows the nonlinear nature of many time series. They do not explicitly determine the minimum time required for a population trend to predict a longer-term trend. Therefore, this article adds to their work by determining the minimum number of years required to determine a population trend. Many populations require far greater than the IUCN rule of 10 years (or three generations) employed by Keith and colleagues (2015).

An important related idea is the optimal allocation of sampling effort spatially. In a theoretical investigation of this question, Rhodes and Jonzen (2011) found that the optimal allocation of sampling depended strongly on temporal and spatial autocorrelation. If spatial population dynamics were highly correlated, it was better to sample more temporally and vice versa. The empirical data supports this idea as

populations with strong temporal autocorrelation needed fewer years of sampling (figure 3). Morrison and Hik (2008) also studied the optimal allocation of sampling effort in space versus time but used empirical data from a long-term survey of the collared pika (*Ochotona collaris*) in the Yukon. They found that surveys less than 5 years may be misleading and that extrapolating from one population to another, even when nearby geographically, may be untenable.

Seavy and Reynolds (2007) asked whether statistical power was even a useful framework for assessing long-term population trends. They examined 24 years of census data on red-tailed tropicbirds (*Phaethon rubricauda*) in Hawaii. They always had .8 statistical power to detect a 50% decline over 10 years. Therefore, they cautioned against only using power analyses to design monitoring schemes and, instead, argued for metrics that would increase precision: improving randomization, reducing bias, and increasing detection probability. Power analyses should not be the only consideration when designing monitoring schemes. However, unlike Seavy and Reynolds (2007), the present results show that at least 10 years of monitoring were required for 72% of populations. Furthermore, 30.7% of populations required at least 20 years of monitoring.

Limitations

This study has some limitations in determining the minimum time series length required. First, the minimum time estimated is particular to the specific question of interest. Specifically, I examined the minimum time required to determine whether a long-term linear population trend exists. The minimum time required would differ if one was interested in examining nonlinear trends (Keith et al. 2015), seasonal dynamics (White and Hastings 2018), assessing multiple populations, or answering a different question altogether. The empirical approach presented in the present article was also limited to only 477 populations of vertebrate species. An additional complication is that the subsampling of the full time series allows for estimates of power, but the individual subsamples are clearly not independent of one another. In an ideal setting, a specific population model would be parameterized for each population of interest. Then, model simulations could be used to estimate the minimum time series required to address each specific question of interest. Clearly, this is not always practical, especially if conducting analyses for a wide array of species.

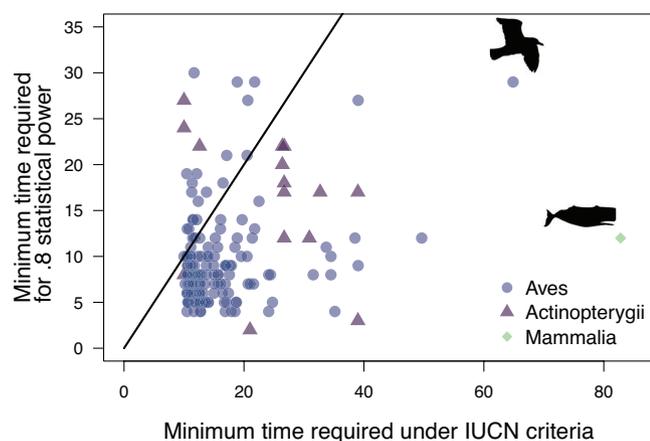


Figure 4. Minimum time required to achieve .8 statistical power versus the minimum time required under IUCN criteria A2 to classify a species as vulnerable. Each point represents a single population, all of which saw declines of 30% or greater over a 10-year period. The silhouettes highlight that species with longer generation times typically have larger discrepancies between T_{\min} and the minimum time required for IUCN assessments.

Conclusions

Power analyses are not a novel aspect of ecological research (Thomas and Krebs 1997, Legg and Nagy 2006). However, power analyses are still underused, especially in the context of time series analyses. This is the first article to address such a large number of populations (822) to determine the minimum time series length required to detect population trends. The present study goes beyond previous work that was focused either on theoretical investigations or on a limited number of species. I show that to identify long-term changes in abundance, on average 15.91 years of continuous monitoring are often required (figure 2). More importantly, however, there is wide distribution of estimated minimum times. Therefore, it is not wise to use a simple threshold number of years in monitoring design. Furthermore, contrary to my initial hypotheses, minimum time required did not correlate with generation time or any other life-history traits (figure 3d–h). These results are evidence against overly simplified measures of minimum sampling time based on generation length or other life-history traits, such as those of the IUCN criteria (figure 4). Instead, simulation models or power analyses should be tailored to particular populations.

The design of monitoring programs should include calculations of statistical power, the allocation of sampling in space versus time (Larsen et al. 2001, Rhodes and Jonzen 2011), and metrics to increase precision (Seavy and Reynolds 2007). Ideally, a formal decision analysis to evaluate these different factors would be conducted to design or assess any monitoring program (Hauser et al. 2006, McDonald-Madden et al. 2010). This type of formal decision analysis would also include information on the costs

of monitoring. These costs include the actual costs of sampling (Brashares and Sam 2005) and the ecological costs of inaction (Thompson et al. 2000).

For many populations, short time series are probably not reliable for detecting population trends. This result highlights the importance of long-term monitoring programs. From both a scientific and management perspective, estimates of the minimum time required are important. If a time series is too short, we lack the statistical power to reliably detect population trends. In addition, a time series that is too long may be a poor use of already limited funds (Gerber et al. 1999). Furthermore, more data is not always best in situations in which management actions need to be taken (Martin et al. 2012, 2017). When a population trend is detected, it may be too late for management action. In these situations, the precautionary principle may be more appropriate (Thompson et al. 2000). Future work should examine other species, with a wider range of life-history characteristics. In addition, similar approaches can be used to determine the minimum time series length required to address additional questions of interest.

Acknowledgments

ERW was partially supported by a National Science Foundation graduate fellowship. I would like to thank members of the Ecological Theory group at the University of California, Davis, for their insight. I would also like to thank Tad Dallas, Emily Malcolm-White and two anonymous reviewers for their insights and helpful criticisms.

Supplemental material

Supplemental data are available at *BIOSCI* online.

In the supplemental material, I have provided an expanded methods sections, additional figures, minimum time calculations for determining exponential growth, simulations with a more complicated population model, the use of generalized additive models to identify population trends, and regressions that correct for phylogenetic relationships. All code and data can be found at <https://github.com/erwhite1/time-series-project>.

References cited

- Blanchard JL, Maxwell DL, Jennings S. 2007. Power of monitoring surveys to detect abundance trends in depleted populations: The effects of density-dependent habitat use, patchiness, and climate change. *ICES Journal of Marine Science* 65: 111–120.
- Bolker BM. 2008. *Ecological Models and Data in R*, 1st ed. Princeton University Press.
- Brashares JS, Sam MK. 2005. How much is enough? Estimating the minimum sampling required for effective monitoring of African reserves. *Biodiversity and Conservation* 14: 2709–2722.
- Cohen J. 1992. A power primer. *Psychological Bulletin* 112: 155–159.
- Felsenstein J. 2008. Comparative methods with sampling error and within-species variation: Contrasts revisited and revised. *American Naturalist* 171: 713–725.
- Field SA, Connor PJO, Tyre AJ, Possingham HP. 2007. Making monitoring meaningful. *Austral Ecology* 32: 485–491.

- Gerber LR, DeMaster DP, Kareiva PM. 1999. Gray whales and the value of monitoring data in implementing the US endangered species act. *Conservation Biology* 13: 1215–1219.
- Gerrodette T. 1987. A power analysis for detecting trends. *Ecology* 68: 1364–1371.
- Gibbs JP, Droege S, Eagle P. 1998. Monitoring populations of plants and animals. *BioScience* 48: 935–940.
- Giron-Nava A, et al. 2017. Quantitative argument for long-term ecological monitoring. *Marine Ecology Progress Series* 572: 269–274.
- Hatch SA. 2003. Statistical power for detecting trends with applications to seabirds monitoring. *Biological Conservation* 111: 317–329.
- Hauser CE, Pople AR, Possingham HP. 2006. Should managed populations be monitored every year? *Ecological Applications* 16: 807–819.
- Hughes BB, et al. 2017. Long-term studies contribute disproportionately to ecology and policy. *BioScience* 67: 271–281. et al. 2017. Long-term studies contribute disproportionately to ecology and policy. *BioScience* 67: 271–281.
- IUCN. 2012. *IUCN Red List Categories and Criteria*. Version 3.1.
- Johnson PC, Barry SJ, Ferguson HM, Müller P. 2015. Power analysis for generalized linear mixed models in ecology and evolution. *Methods in Ecology and Evolution* 6: 133–142.
- Keith D, et al. 2015. Temporal correlations in population trends: Conservation implications from time-series analysis of diverse animal taxa. *Biological Conservation* 192: 247–257.
- Larsen DP, Kincaid TM, Jacobs SE, Urquhart NS. 2001. Designs for evaluating local and regional scale trends. *BioScience* 51: 1069.
- Legg CJ, Nagy L. 2006. Why most conservation monitoring is, but need not be, a waste of time. *Journal of Environmental Management* 78: 194–199.
- Magurran AE, Baillie SR, Buckland ST, Dick JM, Elston DA, Scott EM, Smith RL, Somerfield PJ, Watt AD. 2010. Long-term data sets in biodiversity research and monitoring: Assessing change in ecological communities through time. *Trends in Ecology and Evolution* 25: 574–582.
- Mapstone BD. 1995. Scalable decision rules for environmental impact studies: Effect size, type I, and type II errors. *Ecological Applications* 5: 401–410.
- Martin TG, Camaclang AE, Possingham HP, Maguire LA, Chadès I. 2017. Timing of protection of critical habitat matters. *Conservation Letters* 10: 308–316.
- Martin TG, Nally S, Burbidge AA, Arnall S, Garnett ST, Hayward MW, Lumsden LF, Menkhorst P, McDonald-Madden E, Possingham HP. 2012. Acting fast helps avoid extinction. *Conservation Letters* 5: 274–280.
- McCain CM, Szewczyk T, Knight KB. 2016. Population variability complicates the accurate detection of climate change responses. *Global Change Biology* 22: 2081–2093.
- McDonald-Madden E, Baxter PWJ, Fuller RA, Martin TG, Game ET, Montambault J, Possingham HP. 2010. Monitoring does not always count. *Trends in Ecology and Evolution* 25: 547–550.
- Morrison S, Hik DS. 2008. When? Where? And for How Long? Census Design Considerations for an Alpine Lagomorph, the Collared Pika. Pages 103–113 in Alves PC, Ferrand N, Hackländer K, eds. *Lagomorph Biology*. Springer.
- Myhrvold NP, Baldrige E, Chan B, Sivam D, Freeman DL, Ernest SM. 2015. An amniote life-history database to perform comparative analyses with birds, mammals, and reptiles. *Ecology* 96: 3109.
- NERC Centre for Population Biology Imperial College. 2010. The Global Population Dynamics Database, version 2. <http://www3.imperial.ac.uk/cpb/databases/gpdd>.
- Nichols JD, Williams BK. 2006. Monitoring for conservation. *Trends in Ecology and Evolution* 21: 668–673.
- Paradis E, Claude J, Strimmer K. 2004. APE: Analyses of phylogenetics and evolution in R language. *Bioinformatics* 20: 289–290.
- Peters DP. 2010. Accessible ecology: Synthesis of the long, deep, and broad. *Trends in Ecology and Evolution* 25: 592–601.
- R Core Team. 2017. R: A language and environment for statistical computing.
- Rhodes JR, Jonzen N. 2011. Monitoring temporal trends in spatially structured populations: How should sampling effort be allocated between space and time? *Ecography* 34: 1040–1048.
- Rueda-Cediel P, Anderson KE, Regan TJ, Franklin J, Regan M. 2015. Combined influences of model choice, data quality, and data quantity when estimating population trends. *PLOS ONE* 10 (art. e0132255).
- Seavy NE, Reynolds MH. 2007. Is statistical power to detect trends a good assessment of population monitoring? *Biological Conservation* 140: 187–191.
- Thomas L. 1996. Monitoring long-term population change: Why are there so many analysis methods? *Ecology* 77: 49–58.
- Thomas L. 1997. Retrospective power analysis. *Conservation Biology* 11: 276–280.
- Thomas L, Krebs C. 1997. A review of statistical power analysis software. *Bulletin of the Ecological Society of America* 78: 128–139.
- Thompson PM, Wilson B, Grellier K, Hammond PS. 2000. Combining power analysis and population viability analysis to compare traditional and precautionary approaches to conservation of coastal cetaceans. *Conservation Biology* 14: 1253–1263.
- Wagner T, Vandergoot CS, Tyson J. 2009. Evaluating the power to detect temporal trends in fishery-independent surveys: A case study based on gill nets set in the Ohio waters of Lake Erie for walleyes. *North American Journal of Fisheries Management* 29: 805–816.
- White ER, Nagy JD, Gruber SH. 2014. Modeling the population dynamics of lemon sharks. *Biology Direct* 9: 1–18.
- White ER, Hastings A. 2018. Seasonality in ecology: Progress and prospects in theory. *Peer J Preprints* 6 (art. e27235v1).
- Zuur AF, Ieno EN, Walker NJ, Saveliev AA, Smith GM. 2009. *Mixed Effects Models and Extensions in Ecology with R*. Springer.

Easton R. White (eawhite@ucdavis.edu) is affiliated with the Center for Population Biology at the University of California, Davis.