Title: Minimum time required to detect population trends: the need for long-term monitoring programs

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Abstract

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. When is a population time series long enough to address a question of interest? We determine the minimum time series length required to detect significant increases or decreases in population abundance. To address this question, we use simulation methods and examine 878 populations of vertebrate species. Here we show that 15-20 years of continuous monitoring are required in order to achieve a high level of statistical power. For both simulations and the time series data, the minimum time required depends on trend strength, population variability, and temporal autocorrelation. These results point to the importance of sampling populations over long periods of time. We argue that statistical power needs to be considered in monitoring program design and evaluation. Time series less than 15-20 years are likely underpowered and potentially misleading.

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

1 Introduction

Observational studies and population time series have become a cornerstone of modern ecological research and conservation biology (Magurran et al. 2010; Hughes et al. 2017). Long-term data are necessary to both understand population dynamics and to assess species extinction risk. Even though many time series may now be considered "long-term" (e.g. continuous plankton recorder, Giron-Nava et al. (2017)), most are still short. Time series are typically short for a variety of reasons (Field et al. 2007). They are often coupled with an experiment, which may only last a couple of years. In addition, short funding cycles make it difficult to examine populations over longer periods of time (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). Scientists need to know the time series length required to address a specific question. A short time series may lead to wrong conclusions given large natural year-to-year variability. Managers need to know when action is needed for a population. Therefore, they must understand when population trend over time is actually meaningful. The 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 3 generations (IUCN 2012). For both scientific and management questions, because sampling is typically expensive, we also do not want to sample for longer than is necessary. For example, Gerber, DeMaster, and Kareiva (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, eight years before the delisting decision was made. This highlights the

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importance of estimating the minimum time series required as an earlier decision would have saved time and money (Gerber, DeMaster, and Kareiva 1999).

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 relationship between these quantities depends on the specific statistical test. A type I error is a false positive, or 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 false positive rate, or significance level (α) is often set at 0.05 (although this is purely historical, Mapstone (1995)). A type II error (β) is a failure to detect a true trend, or failure to reject a false null hypothesis. Formally, statistical power ($1 - \beta$) is one minus the probability of a type II error (β). The effect size is a measure of the difference between two groups. Prior to an experiment, one could set appropriate levels of power, significance level, and the effect size to estimate the sample size required for the experiment. This approach, however, is not straight-forward for a time series, or more complicated scenarios (P. C. Johnson et al. 2015), as data are clearly non-independent.

For time series data, two general approaches to estimating sample size are appropriate. Simulations can be designed for a specific population and question (Bolker 2008; P. C. Johnson et al. 2015). Simple models can be simulated with parameter values corresponding to a population of interest (Gerrodette 1987). Statistical power can then be calculated as the fraction of simulations that meet some criteria. The specific criteria depend on the question at hand. For example, given a time series, when is the slope from linear regression significantly different from zero? In other words, when is the time series significantly increasing or decreasing? It is then possible to determine how power changes with a variable of interest. For example, time series can be simulated for different lengths of time. From these simulations, the minimum time series length required is calculated to meet certain levels of statistical significance and power (Bolker 2008).

In addition to using simulations, empirical time series can also be used. Multiple replicates of similar populations are usually not available, but it is possible to subsample an empirical time series (Gerber, DeMaster, and Kareiva 1999). Subsamples of different lengths can then be evaluated to see which fraction of subsamples meet some criteria, again a measure of statistical power. Similar to the simulation approach, these measures of power can be used to determine the minimum time series required for a particular question of interest.

Past work has investigated questions related to the minimum time series required to estimate trends in population size over time (Wagner, Vandergoot, and Tyson 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 et al. (2015) also used a modeling approach, but parameterized a model specifically 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. Hatch (2003) examined seabird populations and determined the minimum time required to achieve high statistical power ranged between 11 and 69 years. However, these studies, and other past work, have typically focused either on theoretical aspects of monitoring design or focused on only a few species.

We use both simulations and empirical time series to determine the minimum number of years required to address several questions. We estimate the minimum time series length required (T_{min}) to assess long-term changes in abundance via simple linear regression. First, we estimate T_{min} using a simulation approach. Then we examine 878 population time series to estimate T_{min}. In the supplementary material, we determine T_{min} for related ideas: calculating long-term growth rates, using more complicated population models, varying statistical level and power, and the use of generalized additive models.

2 Methods

2.1 Simulation approach

One approach to determining the minimum time series length needed is through repetitive simulations of a population model (Gerrodette 1987). This is the same approach one might use in sample size calculations for any experimental design too complicated for simple power analyses (Bolker 2008; P. C. Johnson et al. 2015). We only briefly discuss this approach as it has been described elsewhere. Essentially, we use a population model and repetitively simulate it for a number of years. This approach requires us to determine values for our model parameters (e.g. population variability). As an example, we can take the following population model for population size N at time t:

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

where ϵ is a normally-distributed random noise term with mean μ and standard deviation σ. The rate of growth r is also the trend strength of the increase or decrease (i.e. the rate of increase). It is important to note that any population model could be substituted for equation 1, as we do in the supplementary material (Figs. A6, A7).

Statistical power is then the fraction of simulations that meet some criteria. Here, our criteria is whether the slope parameter from linear regression is significant at the 0.05 threshold. Statistical power of 0.8 would indicate that, if there was a true trend in abundance, we would have a 0.8 probability of detecting the trend. We also tested the effect of varying both the significance level and statistical power (Fig. A5).

In Fig. 1a, a number of simulated time series are shown for a set number of time periods ($t = 40$). It is clear that statistical power increases quickly with increases in length of time sampled (Fig. 1b). Where power is greater than 0.8 (the dotted line), that is the minimum time required (T_{min}).

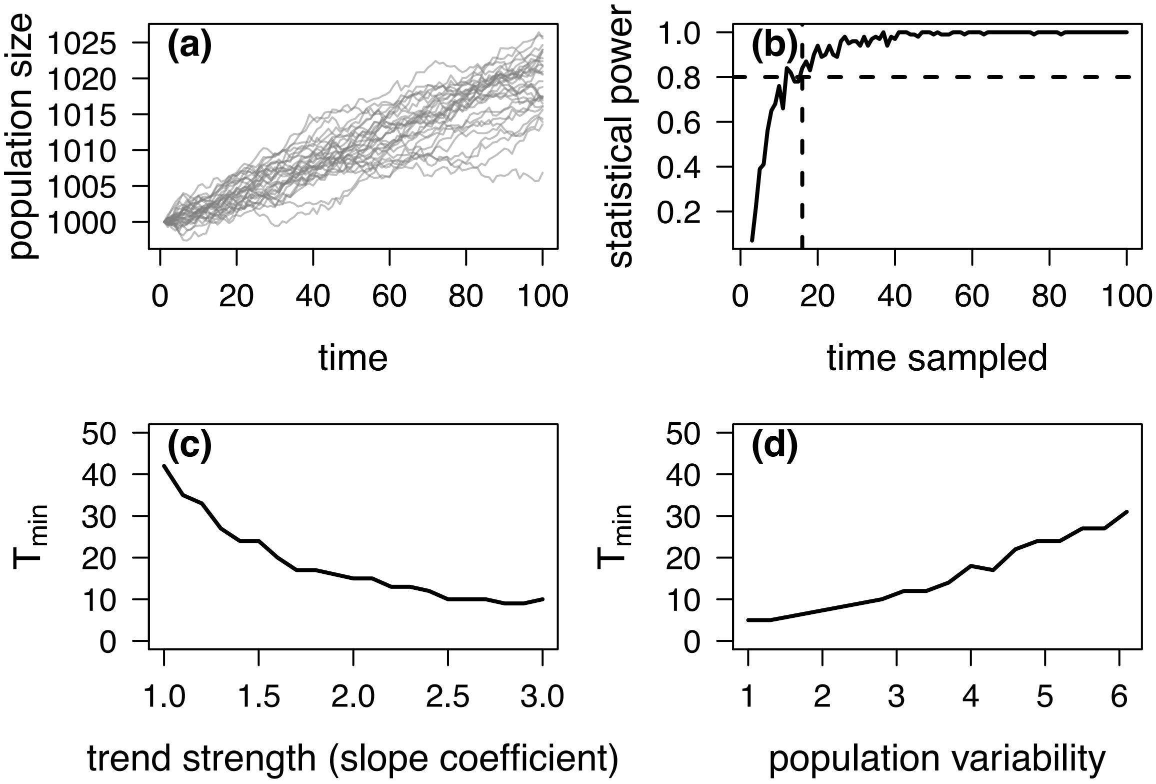

Figure 1: (a) Example of a simulated time series for 40 time periods. (b) Statistical power versus the simulated time series length. The horizontal, dashed line is the desired statistical power of 0.8. The vertical, dashed line is the minimum time required to achieve the desired statistical power. (c) Minimum time required (T_{min}) for simulations with different values of the trend strength (r). (d) Minimum time required for different levels of population variability (σ). In each case, the minimum time required is the minimum number of years to achieve 0.8 statistical power given a significance level of 0.05.

2.2 Data source

We use a database of 2444 population time series compiled in (Keith et al. 2015); they compared the predictability of growth rates among populations. The data are originally from the Global Population Dynamics Database (NERC Centre for Population Biology 2010). We filtered out short time series (less than 35 years), and those with missing data, and were left with 878 time series. The data includes information on 478 vertebrate species with a focus on mammals, birds, and fish. The data also includes information on generation length and census specifications. For each time series, we also calculated variables of interest like variance in population size, long-term trend in abundance (slope coefficient from simple linear regression), and temporal autocorrelation. All analyses were conducted in R (R Core Team 2016).

For a subset of populations ($n = 547$), we had information on biological characteristics from another paper (Myhrvold et al. 2015), including body size and generation length. All 547 populations were birds. We examine how the minimum time required is related to these biological characteristics (Fig. A3).

2.3 Empirical approach

We assume that each time series in our database is long enough to include all necessary information (e.g. variability) about the population. In other words, each time series is a representative sample. We first take all possible contiguous subsamples of each time series. For example, a time series of 35 years would have 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, DeMaster, and Kareiva 1999; Giron-Nava et al. 2017). Next, we run a linear regression for each subsampled time series. Then, we determine the fraction of subsamples of a particular length that have estimated slope coefficients which are statistically different from zero. We only look at the fraction of samples where the long-term, or “true”, time series also has a significant slope. This fraction is a measure of statistical power. Lastly, we determine which subsample length is required to achieve a certain threshold of statistical power (0.8, Cohen (1992)). The subsampled length meeting these criteria is the minimum time series length required (T_{min}).

In the supplementary material, we show how the same approach described here can be used to determine the minimum time required to estimate a population’s geometric growth rate (Figs. A8,A9). We also determine the minimum time required to estimate long-term trends according to generalized additive models, instead of the simple linear models used here (Fig. A10).

3 Results

We determined the minimum time series length (T_{min}) required to address a particular question of interest. What is the minimum time series length required to determine, via linear regression, the long-term population trend? Here, the minimum time series length required had high enough statistical power ($1-\beta$ greater than 0.8) for a set significance level (α) of 0.05. It is also possible to alter $1-\beta$ and α. Predictably, as we increased our level of power or decreased α, T_{min} increased (Fig. A5). We estimated T_{min} using two approaches. We briefly describe results from the simulation approach and then discuss our empirical approach.

3.1 Simulation approach

We constructed a general population model where the trend strength (i.e. slope coefficient) over time could be a model parameter. We then ran simulated time series of different lengths. From these simulations we determined the minimum time series length required to achieve a certain level of statistical power. In line with past work (Gerrodette 1987), we found the T_{min} increases (i.e. more time is required) with decreases in trend strength and with increases in population variability (Figs. 1c,d).

We chose a simple model, but any other population model could be used (see example in Fig. A6). Ideally, the specific model choice should be tailored to the population of interest. We explored how the simulation approach can be applied to more biologically-realistic population models (Fig. A7). More specifically, we 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, Nagy, and Gruber 2014). We found that over 27 years of continuous monitoring were needed in this particular scenario (Fig. A7). Similar to the simulation approach described above, the minimum time required for the lemon shark population was strongly dependent on model parameters.

3.2 Empirical approach

We examined a database of 878 separate population time series representing 478 species. This database consists of vertebrate species with a variety of life history characteristics (Fig. A3). We limited our analyses to populations with at least 35 years of continuous sampling. We then examined the minimum time required to estimate long-term trends via linear regression.

Across all the populations we examined, we found an average minimum time series length required (T_{min}) of 16.5 (σ=8.4), with a wide distribution (Fig. 2). Estimates of T_{min} varied between biological class (Fig. 2). 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 less years of sampling. Differences between these classes were explained by differences in inter-annual variability in population size (Fig. A4). We also examined a

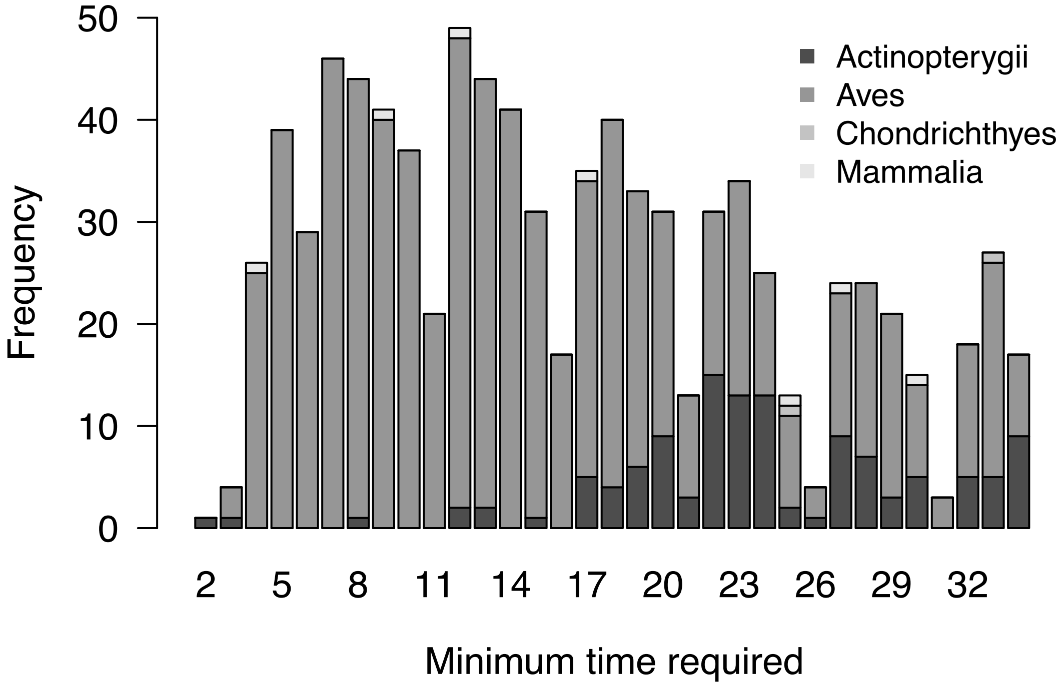

Figure 2: Distributions of the minimum time required for four different biological classes. The minimum time required calculation corresponds to a significance level of 0.05 and statistical power of 0.8.

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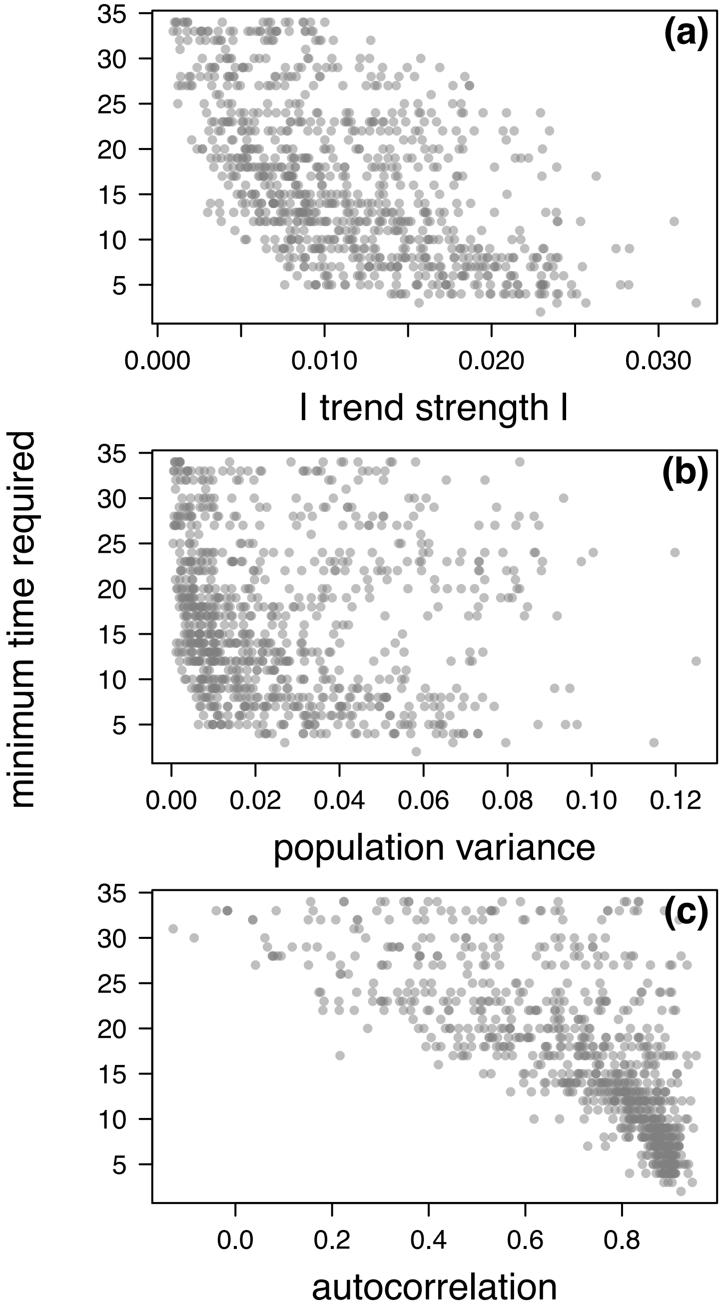

Figure 3: Minimum time required to estimate change in abundance correlated with (a) trend strength (absolute value of slope coefficient estimated from linear regression), (b) population variance (inter-annual variability in population size), and (c) temporal lag-1 autocorrelation.

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subset of populations where life-history characteristics were known. None of these explanatory variables were predictive of the minimum time series length required (Fig. A3).

The minimum time series length required was strongly correlated with trend strength, population variance, and autocorrelation (Fig. 3). This is in line based on our simulations and those of others (Rhodes and Jonzen 2011). Using a generalized linear model, with a Poisson error structure, all three of these explanatory variables were significant and had large effect sizes (see Table A1). Combined, trend strength, population variance, and autocorrelation account for about 72.6% of the explained deviance (Zuur et al. 2009) in minimum time series length required.

Lastly, we tested model sensitivity by using generalized additive models (GAMs) instead of simple linear regression. Again, we examined the minimum time required to estimate long-term population trends (Fig. A10). We found that although we obtain a similar distribution of minimum times required for GAMs, the minimum time required for GAMs is on average shorter than for linear regression (Fig. A11).

4 Discussion

We explored two approaches to estimate the minimum time series length required to address a particular question of interest. We asked, what is the minimum time series length required to determine long-term population trends using linear regression? This is one of the simplest questions one could ask of a time series. The simulation-based approach has been suggested by others, especially in situations more complicated than that suited for classic power analysis (Gerrodette 1987; P. C. Johnson et al. 2015; Bolker 2008). Our simulations support past work that longer time series are needed when the trend strength (i.e. rate of increase or decrease) is weak or when population variability is high (Gerrodette 1987). We also showed how the simulation model can be altered for a particular population (Fig. A7) or question (Figs. A6,A10).

Here, we focus on an empirical approach to estimate the minimum time series length required to assess changes in abundance over time. We examined 878 population time series (all longer than 35 years). We then subsampled each to determine the minimum time required to achieve a desired significance level and power for linear regression. Statistical power is important as it provides on information as to the necessary samples required to determine a significant trend (Legg and Nagy 2006). We found that at least 15-20 years of continuous monitoring were typically necessary (Fig. 2). 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, DeMaster, and Kareiva 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.

In line with theoretical predictions (Rhodes and Jonzen 2011), we also found T_{min} was strongly correlated with the trend strength, variability in population size, and temporal autocorrelation (Fig. 3). Contrary to our prior expectations, we also found that T_{min} did

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not correlate with any biological variables of interest (Fig. A3). We initially hypothesized that species with longer lifespans or generation times may require a longer sampling period. Our result could have been a result of at least two factors. First, the data we used may not include a diverse enough set of species with different life history traits. Second, the question we poised, whether a population is increasing or decreasing, was specifically concerned with trends in population density over time. Therefore, life-history characteristics may be more important for other questions, like estimating species extinction risk (J. A. Hutchings et al. 2012).

An important related question, is the optimal allocation of sampling effort in space versus time. 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, then it was better to sample more temporally, and vice versa. Our work supports this idea as populations with strong temporal autocorrelation needed less years of sampling (Fig. 3). Morrison and Hik (2008) also studied the optimal allocation of sampling effort in space versus time, but used emprical data from a long-term census of the collared pika (*Ochotona collaris*) found in the Yukon. They estimated long-term growth rates among three subpopulations over a 10-year period. They found that censuses 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 used 24 years of census data on Red-tailed Tropicbirds (*Phaethon rubricauda*) in Hawaii and showed that to detect a 50% decline over 10 years almost always resulting in high statistical power (above 0.8). Therefore, they cautioned against only using power analyses to design monitoring schemes and instead argued for metrics that would increase precision. For example, Seavy and Reynolds (2007) suggest improving randomization, reducing bias, and increases detection probability when designing and evaluating monitoring programs. We agree that power analyses should not be the only consideration when designing monitoring schemes. However, unlike Seavy and Reynolds (2007), our results indicate that longer than 10 years is often needed to achieve high statistical power. Therefore, the design of monitoring programs should include calculations of statistical power, the allocation of sampling in space versus time (Rhodes and Jonzen 2011), and metrics to increase precision. Ideally, a formal decision analysis to evaluate these different factors would be conducted to design or assess any monitoring program (Hauser, Pople, and Possingham 2006; McDonald-Madden et al. 2010).

4.1 Limitations

Our work has some limitations in determining the minimum time series length required. First, T_{min} is particular to the specific question of interest. An additional complication is that for our empirical approach, the subsampling of the full time series allows for estimates of power, but the individual subsamples are clearly not independent of one another. Further, estimates of T_{min} depend on chosen values of α and β (Fig. A5). In an ideal setting, we would build a specific population model parameterized for each population of interest. Then,

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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 as we do here. In addition, our statistical models suggest that T_{min} does not correlate with any biological variables of interest, at least for the question of linear regression (Fig. A3). Therefore, it is not possible to use these results to predict T_{min} for another population, even if the population is of a species with a similar life-history to one in our database.

4.2 Conclusions

We use a database of 878 populations to determine the minimum time series length required to detect population trends. This goes beyond previous work that either focused on theoretical investigations or a limited number of species. We show that to identify long-term changes in abundance, 15-20 years of continuous monitoring are often required (Fig. 2). In line with theoretical predictions (Gerrodette 1987), we also show that T_{min} is strongly correlated with the long-term population trend (i.e. rate of increase), variability in population size, and the temporal autocorrelation (Fig. 3). Our work implies that for many populations, time series less than 15-20 years 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 T_{min} are important. If a time series is too short, we lack statistical power to reliably detect long-term population trends. In addition, a time series that is too long may be a poor use of already limited funds (Gerber, DeMaster, and Kareiva 1999). 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.

5 Supporting Information

In the supporting material, we provide an expanded methods sections, additional figures, minimum time calculations for determining exponential growth, simulations with a more complicated population model, minimum time calculations for determining long-term growth rates, and the use of generalized additive models to identify population trends. All code and data can be found at https://github.com/erwhite1/time-series-project

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7 References

Bolker, Benjamin M. 2008. *Ecological Models and Data in R*. 1st ed. Princeton, New Jersey: Princeton University Press.

Cohen, Jacob. 1992. “A power primer.” *Psychological Bulletin* 112 (1): 155–59. doi:10.1037/0033-2909.112.1.155.

Field, Scott A, Patrick J O Connor, Andrew J Tyre, and Hugh P Possingham. 2007. “Making monitoring meaningful.” *Austral Ecology* 32: 485–91. doi:10.1111/j.1442-9993.2007.01715.x.

Gerber, L R, D P DeMaster, and P M Kareiva. 1999. “Gray whales and the value of monitering data in implementing the U.S. endangered species act.” *Conservation Biology* 13 (5): 1215–9.

Gerrodette, Tim. 1987. “A power analysis for detecting trends.” doi:10.2307/1939220.

Giron-Nava, Alfredo, Chase C James, Andrew F Johnson, David Dannecker, Bethany Kolody, Adrienne Lee, Maitreyi Nagarkar, et al. 2017. “Quantitative argument for long-term ecological monitoring.” *Marine Ecology Progress Series* 572: 269–74.

Hatch, S A. 2003. “Statistical power for detecting trends with applications to seabirds monitoring.” *Biological Conservation* 111: 317–29.

Hauser, Cindy E., Anthony R. Pople, and Hugh P. Possingham. 2006. “Should managed populations be monitored every year?” *Ecological Applications* 16 (2): 807–19.

Hughes, Brent B, Rodrigo Beas-luna, Allison K Barner, Kimberly Brewitt, Daniel R Brumbaugh, Elizabeth B. Cerny-Chipman, Sarah L. Close, et al. 2017. “Long-term studies contribute disproportionately to ecology and policy.” *BioScience* 67 (3): 271–81. doi:10.1093/biosci/biw185.

Hutchings, Jeffrey A, Ransom A Myers, Verónica B García, Luis O Lucifora, and Anna Kuparinen. 2012. “Life-history correlates of extinction risk and recovery potential.” *Ecological Applications* 22 (4): 1061–7.

IUCN. 2012. “IUCN Red List Categories and Criteria: Version 3.1.” doi:10.9782-8317-0633-5.

Johnson, Paul CD, Sarah JE Barry, Heather M Ferguson, and Pie Müller. 2015. “Power analysis for generalized linear mixed models in ecology and evolution.” *Methods in Ecology and Evolution* 6 (2): 133–42. doi:10.1111/2041-210X.12306.

Keith, David, H. Resit Akçakaya, Stuart H.M. Butchart, Ben Collen, Nicholas K. Dulvy, Elizabeth E. Holmes, Jeffrey A. Hutchings, et al. 2015. “Temporal correlations in population trends: Conservation implications from time-series analysis of diverse animal taxa.” *Biological Conservation* 192. Elsevier B.V.: 247–57. doi:10.1016/j.biocon.2015.09.021.

Legg, Colin J, and Laszlo Nagy. 2006. “Why most conservation monitoring is, but need not be, a waste of time.” *Journal of Environmental Management* 78: 194–99.

doi:10.1016/j.jenvman.2005.04.016.

Magurran, Anne E, Stephen R Baillie, Stephen T Buckland, Jan Mcp Dick, David A Elston, E Marian Scott, Rognvald I Smith, Paul J Somerfield, and Allan D Watt. 2010. "Long-term datasets in biodiversity research and monitoring : assessing change in ecological communities through time." *Trends in Ecology and Evolution* 25: 574–82. doi:10.1016/j.tree.2010.06.016.

Mapstone, Bruce D. 1995. "Scalable decision rules for environmental impact studies : effect Size , type I , and type II errors." *Ecological Applications* 5 (2): 401–10.

McDonald-Madden, Eve, Peter W J Baxter, Richard A. Fuller, Tara G. Martin, Edward T. Game, Jensen Montambault, and Hugh P. Possingham. 2010. "Monitoring does not always count." *Trends in Ecology and Evolution* 25 (10): 547–50. doi:10.1016/j.tree.2010.07.002.

Morrison, Shawm, and David S. Hik. 2008. "When? Where? And for how long? Census design considerations for an Alpine Lagomorph, the Collared pika." In *Lagomorph Biology*, 103–13. Springer Berlin Heidelberg. doi:10.1007/978-3-540-72446-9.

Myhrvold, Nathan P., Elita Baldridge, Benjamin Chan, Dhileep Sivam, Daniel L. Freeman, and S.K. Morgan Ernest. 2015. "An amniote life-history database to perform comparative analyses with birds, mammals, and reptiles." *Ecology* 96 (11): 3109.

NERC Centre for Population Biology, Imperial College. 2010. "The Global Population Dynamics Database Version 2."

Nichols, James D., and Bryon K. Williams. 2006. "Monitoring for conservation." *Trends in Ecology and Evolution* 21 (12): 668–73. doi:10.1016/j.tree.2006.08.007.

R Core Team. 2016. "R: A language and environment for statistical computing." Vienna, Austria: R Foundation for Statistical Computing. https://www.r-project.org/.

Rhodes, Jonathan R., and Niclas Jonzen. 2011. "Monitoring temporal trends in spatially structured populations: how should sampling effort be allocated between space and time?" *Ecography* 34 (6): 1040–8. doi:10.1111/j.1600-0587.2011.06370.x.

Rueda-Cediel, Pamela, Kurt E Anderson, Tracey J Regan, Janet Franklin, and M Regan. 2015. "Combined influences of model choice, data quality, and data quantity when estimating population trends." *PLoSONE* 10 (7): e0132255. doi:10.1371/journal.pone.0132255.

Seavy, Nathaniel E., and Michelle H. Reynolds. 2007. "Is statistical power to detect trends a good assessment of population monitoring?" *Biological Conservation* 140 (1-2): 187–91. doi:10.1016/j.biocon.2007.08.007.

Wagner, Tyler, Christopher S. Vandergoot, and Jeff Tyson. 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: 805–16. doi:10.1577/M08-197.1.

White, Easton R, John D Nagy, and Samuel H Gruber. 2014. "Modeling the population dynamics of lemon sharks." *Biology Direct* 9 (23): 1–18.

Zuur, Alain F., Elena N. Ieno, Neil J. Walker, Anatoly A. Saveliev, and Graham M. Smith.

2009. *Mixed Effects Models and Extensions in Ecology with R*. New York: Springer.