Sampling requirements and approaches to detect ecosystem shifts

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ABSTRACT

Environmental monitoring is a key component of understanding and managing ecosystems. Given that most monitoring efforts are still expensive and time-consuming, it is essential that monitoring programs are designed to be efficient and effective. In many situations, the expensive part of monitoring is not sample collection, but instead sample processing, which leads to only a subset of the samples being processed. For example, sediment or ice cores can be quickly obtained in the field, but they require weeks or months of processing in a laboratory setting. Standard sub-sampling approaches often involve equally-spaced sampling on depth. We use simulations to show how many samples, and which types of sampling approaches, are the most effective in detecting ecosystem change. We test these ideas with a case study of Cladocera community assemblage indicators reconstructed from a sediment core. We demonstrate that standard approaches to sample processing are less efficient than an iterative approach. For our case study, using an optimal sampling approach would have resulted in savings of 195 person-hours—thousands of dollars in labor costs. We also show that, compared with these standard approaches, fewer samples are typically needed to achieve high statistical power. We explain how our approach can be applied to monitoring programs that rely on video records, eDNA, remote sensing, and other common tools that allow re-sampling.

1. Introduction

Environmental monitoring is one of the core components to modern ecosystem research and management (McDonald-Madden et al., 2010; White, 2019; Lindenmayer et al., 2020). Within an adaptive management framework, monitoring is needed for both learning about the system under study and assessing the effectiveness of management interventions (Lovett et al., 2007). Increasingly, long-term monitoring programs, like the Long Term Ecological Research (LTER) Network in the USA, are becoming available (Maguran et al., 2010). However, environmental monitoring can still be logistically difficult, expensive, and time-consuming, especially when further processing is needed following sample collection (Zhang and Zhang, 2012). Thus, for many fields there is a disparity between the amount of data that can be acquired and stored, and the ultimate number of samples that can be processed. Therefore, monitoring programs need to be designed in such a way to address the question of interest while using limited resources efficiently (Legg and Nagy, 2006; McDonald-Madden et al., 2010; Lengyel et al., 2018; Lindenmayer et al., 2020).

Monitoring program characteristics must be tightly linked to the questions of interest. For example, White (2019) found that 72% of vertebrate populations required at least 10 years of monitoring to detect significant changes in the population size over time. The specific number of years required depended on the species biology and the detection method used (White, 2019). In addition, the sampling effort required differs depending on the question. For example, questions regarding phenology would require many sampling points within a season and across years (Filippa et al., 2015; White and Hastings, 2020). Other work has focused on the frequency of monitoring (Wauchope et al., 2019), the impact of allocating monitoring resources spatially versus temporally (Rhodes and Jonzen, 2011; Weiser et al., 2019), imperfect detection (Morant et al., 2020), and the costs and benefits of increasing sampling breadth relying on citizen science (Weiser et al., 2020). Lastly, both the ecological and economical costs of failing to detect a true trend (type II error) have to be weighed against the risks of false (type I error) detection (Mapstone, 1995). Given limited budgets, monitoring programs need to be designed to be cost-effective (Caughlan, 2001; Gramtham et al., 2008; Bennett et al., 2016).

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Because ecological systems are dynamic in both space and time, it is essential that sampling designs account for spatio-temporal dynamics (Williams et al., 2018). To estimate a particular parameter, e.g., population abundance, optimal spatial sampling strategies are based on spatially balanced sampling (Kermorvant et al., 2019), while optimal temporal sampling strategies are more cost efficient with a targeted sampling, e.g., around the period of reproduction (Jackson et al., 2008). In either case, sampling time and locations can be chosen in an iterative process to be cost-effective and reduce the uncertainty in the process (Hooten et al., 2009). With the ability to choose precisely when to sample, we can move beyond random, interval, or opportunistic sampling designs. This is particularly relevant in situations where a subset of samples already collected need to be analyzed.

Because of new technological advances, there are many data sources that can be derived long after the actual processes occurred. For example, sediment cores can be retrieved from aquatic ecosystems with little sediment disturbances, such as lakes or lagoon, allowing reconstruction of past ecological communities or conditions (Cohen, 2003). Similarly, environmental samples (e.g. water, soil) can be saved and processed later for composition, including eDNA (Bohmann et al., 2014). Likewise, photo- or video-based monitoring can record snapshots of a system and be analyzed later (O’Connell et al., 2011; Mallet and Pelletier, 2014). In each of these cases, decisions have to be made about how much data to extract from the previously collected samples (Zhang and Zhang, 2012). Should the paleoecological core be analyzed at every centimeter? Should the video be assessed once per minute if automated sampling is not used? The iterative process can be used to refine the sampling strategy until the desired level of accuracy is achieved.

Fig. 1. Conceptual diagram illustrating the process of taking (a) simulations of a time series and (b) selecting a single simulation to analyze with three different sampling approaches: (c) random, (d) regular, and (e) iterative. The iterative sampling approach requires (f) adding samples around a detected changepoint until (g) a certain level of accuracy is achieved.

![Fig. 1. Conceptual diagram illustrating the process of taking (a) simulations of a time series and (b) selecting a single simulation to analyze with three different sampling approaches: (c) random, (d) regular, and (e) iterative. The iterative sampling approach requires (f) adding samples around a detected changepoint until (g) a certain level of accuracy is achieved.](image-url)
Sampling approaches and changepoint detection

For both our simulations and case study, we investigate the effect of different sampling strategies on our ability to detect a changepoint. We begin by either creating simulated time series or using an actual paleoecological time series (Fig. 1). We then subsampled each time series to test the effect of three different sampling approaches along with varying the sample size (Fig. 1c–f). We compared the estimated changepoint from the subsampled time series to that of the full time series as a measure of the effectiveness.

The random sampling approach involves taking a set number of random points throughout the time series (Fig. 1c). In the context of sediment cores, this would mean analyzing community composition at random locations along the core. Random sampling is recommended in designs aimed at quantifying the average size of a population (spatial approach) (Nad’o and Kanuch, 2018). We hypothesize that random sampling will perform the worst in estimating the changepoint. Regular sampling is commonly used (e.g., pigments in Milan et al., 2015) and requires that a set number of samples be taken at regular intervals (Fig. 1d). Lastly, iterative sampling involves first taking a set number of samples (i.e., regular sampling) and then iteratively adding samples until a predetermined level of precision is achieved (Fig. 1e–g). In the context of a changepoint, this means adding a new sample near the best estimate for the changepoint and iteratively updating the estimate (Fig. 1e–g). For each scenario, we begin by sampling the first and last sample to ensure coverage of the whole time period. We describe each approach in more detail in the supplementary material and provide code.

We detect changepoints with the function e.divisive in the R package ecp (James et al., 2019). There are several methods available to detect changepoint (reviewed in James and Matteson, 2014); e.divisive is a divisive hierarchical estimation algorithm for multiple changepoint analysis. We chose this method because it is able to perform multiple change point analysis for both uni- and multi-variate time series, without a priori knowledge of the number of changepoints. Herein, we focus on detecting the most important changepoint (i.e. the one of largest magnitude), although we tested the method on a time-series that would have multiple changepoints (Fig. S3). In order to test the performance, we detected the “true” changepoint on the whole time-series, and compare the changepoint found on the sub-sample with the “true” one. The distance to true changepoint served as the performance diagnostic.

3. Simulation approach

3.1. Simulation model

We began with a theoretical exploration of the sampling requirements to detect a changepoint. We modeled a simple first order autoregressive (AR-1) process (the discrete-time version of the Ornstein–Uhlenbeck process) with a response variable (X_t) that represents either population size, biodiversity, or some other unidimensional metric of community composition at time t. The model includes temporal autocorrelation (ϕ), the mean of the process (μ_x), and a white noise term (w_t). The white noise term is a normal distribution with mean (μ_w) and variance (σ^2):

\[ X_t = \mu_x + \phi(X_{t-1} - \mu_x) + w_t \sim \text{Normal}(\mu_w, \sigma^2). \]  

We included a changepoint by shifting μ_x at time τ given a specific shift size (δ).

Fig. 2. Regular sampling statistical power (fraction of 100 simulations which detected a changepoint within five time points of the true changepoint) for different levels of standard deviation (σ), lag-1 autocorrelation (ϕ), and shift size (δ). For each parameter combination, 20 samples were used. An increase in samples would increase the statistical power across this graph.
We explored how each of these model parameters affected our ability to detect a change point. We simulate an entire time series to serve as the “true” data for comparison (White and Bahlai, 2020). We specifically study how the number of samples and the type of sampling affects the detection probability. For simulations, statistical power is the fraction of simulations that were able to detect a changepoint. We define an accurate changepoint detection if an estimate is within five time points (given a time series of 100 time points) of the true changepoint. The minimum number of samples required is the number needed for 0.8 statistical power.

3.2. Simulation results

In line with theory on optimal monitoring, we found that the probability of correctly identifying a changepoint decreased with smaller levels of population variability ($\sigma$) and autocorrelation ($\phi$) (Fig. 2). We also found that the probability of correct changepoint detection increases with larger shift sizes, which is essentially the effect size (Fig. 2). In line with theory, if the shift size was small, and thus there was no changepoint, there was almost never enough power to detect a shift. Similar results have been shown for the detection of linear trends (White, 2019). There were interaction effects between the variables. For example, autocorrelation was only important if population variability was high (Fig. 2). Thus, the number of samples required to obtain high statistical power (above 0.8) increased with larger population variability, lower autocorrelation, and smaller shift sizes (Fig. 3). As predicted, iterative sampling performed best, followed by regular and random sampling (Fig. 3). The distance to the true changepoint, and consequently the minimum number of samples required, was lower for iterative sampling. (Fig. 3).

4. Case study

4.1. Case study background

We examined the performance of our approach to detect change points in a paleosequence. Paleolimnology allows to reconstruct past environments over long periods of time, under the premise that...
sedimentation was not perturbed (low mixing and disturbances). A sediment core is typically subsampled to narrow down periods of time to be compared, either at regular intervals (e.g., Milan et al., 2015), or continuously (e.g., Perga et al., 2015).

We tested different sampling methods on a real community time series from Lake Varese (IT), with the objective to detect the main changepoint in zooplankton Cladocera assemblage. Lake Varese is a small (14.8 km$^2$), deep ($z_{max} = 26$ m), monomictic lake, in the subalpine region of north-western Italy (238 m asl). It underwent hypertrophication over the 20th century due to increase in nutrient loads from the watershed. Nutrient status was responsible for restructuration of the lake communities across trophic levels (Crosta, 1999; Bruel et al., 2018). Air temperature is now driving changes in plankton communities (Bruel et al., 2018).

In a previous study, Cladoceran assemblage was reconstructed continuously with a 1-cm subsampling resolution (2–3 years resolution), from a 74-cm sediment core covering the 1816($\pm$26)—2010 time period (Bruel et al., 2018). Our objective was to evaluate whether the same changepoints could be identified using fewer samples. In this previous study, the variability in the community was summarized into independent axis using Detrended Component Analysis (Hill and Gauch, 1980). Changepoints were then detected on the first component (46% of the total variability) in years 1926, 1946, and 1983. We defined these as the "true" changepoints given they came from an analysis of the complete sequence. The 1983 changepoint was the largest in magnitude, hence the changepoint we sought to find with our method. We also identified second and third changepoints (Fig. S3).

In line with our simulation approach, we subsampled the full record (74 observations) using the three methods described earlier (random, regular, iterative). These subsamples were from the initial community dataset (Fig. 6a). We reduced the dimensionality of the assemblage-level data to an ordination axis using the same method in the original study, and detected the changepoint on the first component (univariate vector). In the case of the iterative method, a new sample was added in the temporal region closest to the estimate for the changepoint until a more precise estimate was obtained (Fig. 6d). For each of the three methods, we examined the error (difference between the true changepoint and the detected changepoint) when using different numbers of samples.

4.2. Case study results

We found that random sampling performed the worst, as changepoint analysis was left to chance (Fig. 5). Regular sampling provided good estimates from 8 samples, but detecting the true changepoint depended on the interval falling close to the true changepoint (i.e., also left to chance). Iterative sampling performed the best, as no more than 9 samples were ever necessary to detect the true changepoint (Fig. 5c). We show how iterative sampling slightly changes the scores on the first component but not the overall ordination, as more samples are added (Fig. 6).

We also tested how the three methods performed at detecting other changepoints of lower magnitude (as three changepoints were detected in the initial study, Bruel et al., 2018). Iterative sampling still performed best, especially if a higher number of initial samples (7) was chosen (Fig. S3).

To show the generality of our approach, we examined the same sediment core data, but examined total abundance as opposed to community composition (Fig. S4). We tested the three subsampling methods, and it took 11 samples to find the "true" changepoint (Fig. S5). The initial 5 subsamples analyzed were the same than the subsamples analyzed to answer the question of the change in community (Fig. S5). The implication is that a very limited number of processed sample can rapidly and efficiently be used to narrow down different questions on a same dataset. In addition, we examined the same abundance time series, but with linear and generalized additive models (GAMs). In line with findings from White (2019), we found that the flexibility of GAMs allow the use of less samples (Figs. S6, S7).

5. Discussion

Due to time or funding limitations, there is often a difference between the number of samples collected and the total number of samples that can later be processed. When the processing time is disproportionately higher than the collection time especially, a subsampling can be done prior to processing. A decision must then be made as to which subsamples to analyze. To address this question in the context of detecting changepoints, we tested three subsampling methods: subsampling random points, regular intervals, and an iterative sampling approach (Fig. 1). We found that the iterative method was systematically better at detecting changes than the two other methods, random subsampling being the least efficient (Figs. 4, 5, S1, S2). Autocorrelation, variance, and shift size, had an effect on how many samples were needed to detect the shift, but did not change which approach was optimal (Fig. 3).

Multiple subsampling strategies can be chosen (Fig. 1), but only iterative sampling detected the true changepoint with a limited number of samples (Fig. 4c). Analyzing 11% of the sample was enough in most cases to approach the "true" changepoint. Applied to the real case study,
the iterative method allowed us to find the main changepoint with only 9 samples analyzed (Fig. 5). The method also worked well to detect other changepoints of lower magnitude (Fig. S3). Bruel et al. (2018) processed one sample at each centimeter in a 74-cm sediment core. Each sample took an average of 3 h to process. We found that using an iterative approach would have eliminated 195 h of sample processing, or about 24 days, which is just a little over a month of work. This correspond to several thousands of US dollars depending on labor costs.

Our approach goes beyond just paleoecological analyses. Running simulations or using past data to understand the amount of sampling effort required is important in many systems where sample collection or processing is expensive (White, 2019; White and Bahlai, 2020) or logistically difficult, such as with remote field sites. The specific sampling techniques can also be compared to determine the optimal strategy in terms of accuracy and cost. Similarly, in order to evaluate ecosystem phenology, Filippa et al. (2015) used similar techniques to show the effect of not only different levels of sampling, but also the effect of using different indices altogether. Our specific approach applies to situations where more subsamples can be added, or processed, after the dynamics occurred (Zhang and Zhang, 2012). It corresponds very well to paleoecological data: samples are taken long after the phenomenon of interest occurred, and allows subsampling at finer or rougher intervals (Wingard et al., 2017). However, both different types of data and different questions than those used here can be addressed with the same approach.

Suppose instead that the goal was to detect a change in relative abundance over time with video-based approaches where automated techniques are not possible. It is often not practical to watch entire videos, so it can be useful to choose strategic time-points that would address a specific question of interest. Using an interval sampling approach, one could take a fixed number of samples to start. The trend over time from simple linear regression could be taken. Then, samples can be taken at random locations one-by-one and to see which samples have the largest effect on the trend estimates. If a particular sample has a large effect on the trend, then it would be best to choose another nearby sample.
Sampling would continue until the trend estimate reached an equilibrium. Thus, the iterative sampling approach is particularly relevant to data sources where additional samples can be taken long after the initial dynamics. These approaches would also be appropriate for environmental samples, such as water or soil, that can be analyzed later or eDNA that can be extracted from previously-collected samples (Bohmann et al., 2014). The same approaches could also be used in studying evidence of stressors found in tree rings or coral reef cores (Carrili et al., 2012; Pretzsch et al., 2013), pollen in aerial traps or sediment cores to address phenological questions (Haselhorst et al., 2013), and many other situations described in White and Bahalai (2020).

Our approach is applicable to a wide range of systems and questions, but it does have limitations. When less resources are needed for sample analysis, as opposed to collection, investigators will likely be able to process every sample, and analyzing all samples to obtain a whole picture may be preferred. We note that if resources need to be saved by collecting less samples in the first place, then regular sampling performs better than random sampling (Figs. 4, S1, S2). Our specific iterative approach for detecting changepoints is also not appropriate for systems where changepoints are not expected. Instead, more flexible models (e.g., GAMs) might be more appropriate (Fig. S7). Another example where our method is less useful is when addressing questions that require a continuous time series, or at least a regular sampling interval. For example, continuous, high-resolution subsampling of a time-series is generally required to detect critical slowing-down or early warning of shifts (Frossard et al., 2015; Doncaster et al., 2016).

However, recent work suggest that combining indicators (in the specific study, trait dynamics and abundance-based early warning signals) allows forecasting population collapses even with at lower resolution and time-series length (Arkilanian et al., 2020). Critical slowing down does not necessarily result in a shift, and a shift can occur without critical slowing down (Spears et al., 2017). Signs of critical slowing down are important to understand and recognize because they provide potential early warnings (Doncaster et al., 2016), but in terms of management, knowing the timing of a shift can have larger implications in addressing the underlying driver. Thus, selecting a set number of samples or specific approach may also limit what future questions can be asked.

6. Conclusions

Analyzing a subsample of a time series as opposed to the whole time series will inevitably lead to a lesser understanding of the phenomenon observed (White, 2019). We show here that an informed subsampling can still allow detection of critical information, such as a changepoint in a time series. Monitoring programs have to be able to address our questions of interest with sufficient statistical power. In addition, optimizing sampling efforts is valuable given the high costs of many monitoring programs (Caughlan, 2001; Bennett et al., 2014). Thus, costs of monitoring have to weighed against the value gained from monitoring—a value of information approach (Lovett et al., 2007; Bennett et al., 2018). Monitoring programs should try to anticipate the potential questions of tomorrow, and reducing the data collected, or analyzed, must be done with the best foresight possible on how these data may be necessary to manage ecosystems in the future. If only a subsample of the samples can be analyzed, it may be better to choose samples strategically as opposed to random or regular sampling. This can improve the accuracy of the results and reduce costs overall.

7. Data availability

Data and code for all the figures can be found at https://github.com/rosalieh/temporal-sampling.

CRediT authorship contribution statement

Rosalie Bruel: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. Easton R. White: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ecolind.2020.107096.

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