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Impacts of temporal revisit designs on the power to detect trend with a linear mixed model: An application to long-term monitoring of Sierra Nevada lakes

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ABSTRACT

Long-term ecological monitoring programs often use linear mixed models to estimate trend in an ecological indicator sampled across large landscapes. A linear mixed model is versatile for estimating a linear trend in time as well as components of spatial and temporal variation in the case of unbalanced data structures, which are common in complex monitoring designs where limited sampling effort must be optimized over time and space. A power analysis was used to inform a lake chemistry monitoring design, including selecting the most appropriate temporal revisit design. Pilot data from surveys of lakes across large wilderness national parks (Sequoia, Kings Canyon, and Yosemite national parks) were used to obtain variance components for a Monte Carlo power simulation. Using a linear mixed model for a range of temporal revisit designs, sample sizes, and trend magnitudes, we evaluated the power to detect trend, the trend test size, and the relative bias of trend coefficient estimates for four continuous and normally distributed indicators. Contrary to prior research based on large-sample approximations that identified a single panel of sites visited annually as the revisit design generating the highest power, we found that the power to detect a 12-year trend based on the Wald t-test from a linear mixed model may be optimized by obtaining unbalanced data sets with limited to no annual replication. We emphasize the importance of examining variance composition, sample size, and the power and size of the trend test with Monte Carlo simulation when allocating sampling effort over time and space.

1. Introduction

Increasing concerns about impacts of global change on natural resources motivate the implementation of long-term monitoring programs to periodically assess resource condition. Land-management agencies, mandated by federal laws such as the Clean Air Act (Public Law 91-604), the Clean Water Act (Public Law 91-662), and the National Parks Omnibus Management Act of 1998 (Public Law 105-391) to monitor natural resources, often implement long-term surveys to track specific environmental indicators over time (Diaz-Ramos et al., 1996; Fancy et al., 2008; Laustrup and Wlosinski, 1991). In 2001, the National Park Service (NPS) initiated a long-term ecological monitoring program, the Vital Signs Monitoring Program, to monitor targeted physical, chemical, and biological indicators of park health over time and space (Fancy et al., 2008).

Trend analysis is used to detect, quantify, and assess the significance of gradual and sustained changes in an outcome over time (Urquhart et al., 1993). We adopt the understanding that trend in an indicator over time may not be strictly linear, but change consisting of a substantial linear component is often relevant to natural resource management (Urquhart and Kincaid, 1999). This linear increase or decrease over time is the trend metric of interest here. Natural resource managers are often tasked with the challenge of managing resources across expansive landscapes. Long-term monitoring ideally allows for broad-scale inference over a population of interest rather than the estimation of a localized trend at a specific site (Urquhart et al., 1998), where a site represents a spatial sampling unit defined as a point or an areal unit. Suites of indicators may be collected at a site and common trends among those indicators may be examined in a multivariate context with modular artificial neural networks (Wu et al., 2010), multivariate Mann-Kendall trend test (Lettenmeier, 1988), and dynamic factor analysis (Zuur et al., 2003). In this research we focus on univariate analysis trend analysis tools.

Information from status and trend analyses may be used to inform

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local management decisions and state and federal environmental policy (Fancy et al., 2008; Nichols and Williams, 2006). Land-management agencies must often balance dual goals of characterizing the current status and temporal trend in indicators of resource condition. The status of an indicator is usually calculated within a particular time frame, often annually, and provides an estimate of the indicator's condition. Status of an ecological indicator is frequently represented by a mean, proportion, percentile, or total (Kincaid and Olsen, 2012). In this work, our primary objective is to detect linear trends in the mean of an indicator using a linear mixed model.

Linear mixed models have been applied to a diverse range of outcomes including guillemot abundance (Sims et al., 2006), gazelle density (Piepho and Ogutu, 2002), salmon habitat characteristics in Pacific Northwestern streams (Larsen et al., 2004), and lake measurements of chlorophyll-a (VanLeeuwen et al., 1996). The linear mixed model of Piepho and Ogutu (2002) provides a flexible framework for linear trend estimation while accounting for sources of variation specific to the system of interest. The Piepho and Ogutu model has been applied to trend analyses of indicators of forest health (Perles et al., 2014), prairie grass seed establishment (Carrington, 2014), bull trout abundance (Meyer et al., 2014), and salmonid habitat (Anlauf et al., 2011). The linear mixed model provides a useful basis for trend inference from multiple sites because the spatio-temporal replication can be used to model the correlation among observations collected within the same year and/or site. Failure to account for correlation in space and time may cause underestimation of the standard error of the trend estimate and erroneous trend inference (Zuur et al., 2007).

Assume that a probabilistic sample consisting of n total observations is obtained from annual samples of s sites, for T years in the monitoring period, and m visits to a site within a given year. Let i index sites, j index years, and k index within-year visits to a site. For "unbalanced" revisit designs in which all sites are not visited every year, the number of years that each site is visited varies so that $n \neq s \times T \times m$; indexing can reflect this imbalance accordingly. We assume that all sampling units contributing to the trend estimate are selected probabilistically and with equal probability. A weaker assumption for general modeling asserts that model-based inference is valid if sites are selected irrespective to the value of the outcome of interest at each site (Schreuder et al., 2001). However, we recommend probabilistic sampling as a defensible basis for unbiased population-level inference.

The general linear mixed model proposed by Piepho and Ogutu (2002) is as follows:

$$y_{ijk} = \gamma_0 + w_j\gamma_1 + b_j + a_i + w_j t_i + c_{ij} + e_{ijk},$$

where $i = 1, \ldots, s$; $j = 1, \ldots, T$; $k = 1, \ldots, m$; and

y_{ijk} = the natural-log transformed outcome of interest for the k^{th} replicate measurement in the i^{th} site in the j^{th} year;
w_j = integer representing j^{th} year (covariate);
γ_0 and γ_1 = fixed intercept (status) and slope (trend) effects of the linear trend model;
a_i = random effect for the i^{th} site, independent and identically distributed as $N(0, \sigma^2_{site})$;
b_j = random effect for the j^{th} year, independent and identically distributed as $N(0, \sigma^2_{year})$;
t_i = random slope for the i^{th} site, independent and identically distributed as $N(0, \sigma^2_{slope})$;
c_{ij} = random interaction term of the i^{th} site and j^{th} year, independent and identically distributed as $N(0, \sigma^2_{int})$; and
e_{ijk} = unexplained error, independent and identically distributed as $N(0, \sigma^2_e)$.

We applied a natural logarithm transformation to the outcome of interest to obtain a useful estimate of multiplicative trend as well as to mitigate increasing variation in residuals, as is often observed for ecological indicators. The fixed effects vector is defined as $\gamma = \{\gamma_0, \gamma_1\}$ where γ_0 represents the baseline status and γ_1 is the linear trend coefficient of the log-transformed indicator. Therefore, $\gamma_1 = \log(1 + \lambda)$, where $100 * \lambda$ is the percentage change observed each year. For example, a 4% annual increase in the population mean corresponds to a value of $\lambda = 0.04$, and a 4% annual decrease in the population mean implies $\lambda = -0.04$. The proportional annual trend on the original scale of the indicator is calculated as $\lambda = \exp(\gamma_1) - 1$, where the subtraction of 1 yields a positive estimate for increasing proportional annual trend and a negative value for decreasing proportional annual trend.

The fixed effects are calculated with generalized least squares estimation (Piepho and Ogutu, 2002). If additional site-level covariates are available, the fixed effects vector could be modified to include these predictors. For example, if opposing trends occurred in different elevational classes, including an interaction term for elevational classes and the fixed year term would provide useful trend inference. Linear population-level trend on the transformed scale is estimated by the fixed slope effect, γ_1, which provides an average of site-level trends for an estimate of trend across the entire population. Site-specific trends may be obtained by adding the estimate of the random site-level slope effect of site i to the population-level trend estimate ($\gamma_1 + t_i$). Ecologically, this captures spatial variation in site-level trends which can be meaningful as this variation is likely related to environmental heterogeneity that is informative to natural resource managers. The standard error of the site-level trend estimate is a function of the fixed and random effects design matrices, the estimated variance of the outcome y_{ij}, and the variance component for random slope variation, σ^2_{slope}(Verbeke and Molenberghs, 2000). The significance of the estimated trend is assessed with the Wald t-statistic using the standard error obtained from the restricted maximum likelihood (REML)-estimated variance components. The Wald t-test demonstrates nominal test size when data are unbalanced and Satterthwaite (1946) degrees of freedom are used (Piepho and Ogutu, 2002), so this test is desirable when examining the power of trend tests for data collected under various revisit designs.

The random effects portion of the mixed model partitions the error term into variance components, including random site effects (a_i) and coherent year effects (b_j) (Urquhart et al., 1993), a random site-by-year interaction (c_{ij}) (Urquhart and Kincaid, 1999), and a random slope effect for each site (t_i) (Piepho and Ogutu, 2002; VanLeeuwen et al., 1996). When the random intercept and slope for a site are modeled jointly as multivariate normal random vectors with $\mathrm{Cov}(a_i, t_i) = \sigma_{at}$, the estimate of the site-to-site variance, σ^2_{site}, is the same regardless of how the w_j are defined. This assumption results in an invariant trend test, which does not change with shifts in the time covariate (Piepho and Ogutu, 2002).

Trend models may also include a site-by-year interaction term (c_{ij}) when sites are visited on multiple occasions within the same year. Visiting a larger number of unique sites may be a better use of sampling effort than within-year replication (VanLeeuwen et al., 1996), so we do not include those terms here and assume at most a single annual visit to a site ($m = 1$). When within-year visits are not an option, such as with remote sites or populations sensitive to excessive trampling, ephemeral variation due to random site-by-year interaction (σ^2_{int})is inestimable and absorbed by the residual error ($\sigma_e{}^2$). However, random slopes, which are the linear component of the random site-by-year interaction (VanLeeuwen et al., 1996), are estimable without replication within a site and year.

The ability to accurately and precisely detect a desired trend in the population of interest may be assessed with a statistical power analysis. Power analysis is a useful tool in aiding development of sample designs and determining how best to allocate limited resources to meet status and trend monitoring objectives. Given that a hypothesis test preserves nominal test size (i.e., the test reflects the nominal Type I error rate, α), statistical power may be assessed to determine if a proposed monitoring plan will meet trend detection objectives. For long-term monitoring, the cost of a Type I error may be far less than the cost of a Type II error.