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A Monte Carlo method to account for sampling error in multi-species indicators

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ABSTRACT

The usefulness of biodiversity indicators strongly increases if accompanied by measures of uncertainty. In the case of indicators that combine population indices of species, however, the inclusion of the uncertainty of the species indices has shown to be hard to realize, usually due to imperfections in monitoring programmes. Missing values and time series of different lengths preclude the use of analytical approaches, whereas bootstrapping across sites requires the raw abundance data on the site level, which may not always be available. Sometimes bootstrapping across species rather than sites is opted for, but this approach ignores the uncertainty attached to species indices. We developed a method to account for sampling error of species indices in the calculation of multi-species indicators based on Monte Carlo simulation of annual species indices. The construction of confidence intervals enables various trend assessments, like testing for linear or smooth trends, testing for changes between two time points, testing the significance of a suspected change-point and testing for differences between two multi-species indicators. Here, we compare our method with conventional methods and illustrate the benefits of our approach using Dutch breeding bird indicators.

1. Introduction

In order to realize the international ambition to slow and eventually halt the ongoing global decline in biodiversity, as expressed in the context of the Convention on Biological Diversity (Butchart et al., 2010; Secretariat of the Convention of Biological Diversity, 2014), it is indispensable to have reliable instruments to measure progress towards set targets. Biodiversity indicators are increasingly used to monitor trends in biodiversity at various habitats and scales (Biala et al., 2012; Butchart et al., 2010; Szabo et al., 2012; Van Strien et al., 2016), the most popular being the combined population trends of individual species (Brereton et al., 2011; Freeman et al., 2001; Gregory et al., 2005; Loh et al., 2005). Such multi-species indicators (MSI) have the advantage of being relatively insensitive to the fluctuations of individual species, thus helping scientists, conservationists and decision makers to better understand the dominant factors influencing biodiversity in a region, country, continent or the entire biosphere. Until now the development of MSIs has mainly focused on methods to calculate the mean index of species, of which the geometric mean of species indices appears one of the most appropriate to use (Buckland et al., 2005, 2011; Lamb et al., 2009; Van Strien et al., 2012). Popular examples of MSIs include the global Living Planet Index (Collen et al., 2009; Loh et al., 2005), the European Grassland Butterfly Indicator (Van Swaay et al., 2013), and the European Wild Bird Indicators (Gregory et al., 2005; Gregory and Van Strien, 2010).

The usefulness of MSIs and trends in MSIs is strongly increased if accompanied by proper measures of uncertainty. Without these, it becomes problematic to test whether changes in the indicator are statistically significant and/or to test the found trend against other indicators. The main sources of uncertainty in MSIs are sampling error and process noise. Sampling error refers to the uncertainty of the species indices, which in most monitoring programmes must be considered as “sampling error in a broad sense”: the “pure sampling error” caused by sampling only part of the population, complemented by sources of variation like measurement bias, imperfect detection and missing values. This part of the variation in time series is also called “observation error” (e.g. Dennis et al., 2006). Process noise refers to the interannual variation between indices, the “process” being the trend in population numbers which usually is the main objective of a monitoring programme. Surprisingly, although the sources of uncertainty of MSIs are

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theoretically well-known it often proves a challenge to construct confidence intervals (CIs) for both MSIs and trends therein that take into account both sampling error and process noise. We know of three common methods, none of which is completely satisfying:

(1) CI based on bootstrapping across species

In this approach (for instance Collen et al., 2009; Craigie et al., 2010; Eaton et al., 2016) the trend of each species is considered as a replicate of the MSI. This approach is useful to assess the robustness of the MSI against species selection, but it neglects sampling error in the species indices. In addition, it suffers from a conceptual drawback: it is questionable to include interspecific variation in the confidence intervals of MSIs. The rationale of testing against variation between species is that the species are randomly sampled from a large group, but this rationale is unjustified as species to represent an MSI are typically deliberately selected. In addition, bootstrapping species may yield wide confidence intervals if the trend of even a single species deviates from the trend of the other selected species for the MSI. Consequently, even evident shifts in the mean of the MSI may remain statistically insignificant.

(2) CI based on interannual variation

This approach is used for the European Wild Bird Indicators and the Living Planet Index (Butchart et al., 2010; Gregory and Van Strien, 2010; Loh et al., 2005), amongst others. Again, in these indicators sampling error is neglected and confidence intervals for trends in MSIs only include the interannual variation. For the European Wild Bird Indicators (Gregory et al., 2005) an analytical approach is presented to calculate CIs for the MSI that takes into account sampling error. However, this approach cannot be extended to trend assessments and it fails whenever a species index is missing for a particular year. Thus, as is the case for other indicators, sampling error is neglected in the trend assessment for European Wild Bird Indicators, even when available. The latter is inevitable, as the TrendSpotter software used for trend calculation cannot include standard errors of yearly MSIs (Soldaat et al., 2007; Visser, 2004). TrendSpotter can efficiently model flexible trends and their CIs by applying the Kalman filter. Unfortunately, only relative weighting factors can be attached to the MSIs. Absolute weighting factors like the standard errors of the MSI would not lead to proper CIs for the calculated trends.

(3) CI based on bootstrapping of sites

This approach properly takes into account sampling error and can be applied in a randomized monitoring scheme like the British Farmland Bird Indicator (Freeman et al., 2001). Bootstrapping on the site level, however, cannot be applied if sites are not a random sample of the population, as in many volunteer-based monitoring programmes. Obviously, bootstrapping of sites can also not be applied when data are not available on the site level, for example when MSIs are constructed using time series obtained from the literature (as in the Living Planet Index) or from national reports (as in the European Wild Bird Indicators).

An approach to take into account sampling error in MSIs that, to our knowledge, has not been explored so far is the use of standard errors of the species indices. In this paper we describe Monte Carlo procedures to generate confidence intervals for MSIs and trends in MSIs based on the standard errors of species indices. The method overcomes the above-mentioned conceptual and practical obstacles, and offers several opportunities for testing and comparing trends in MSIs. Here, we first use conventional approaches to calculate an MSI with confidence intervals from an ideal simulated data set, without missing values. Subsequently, we apply our method to the same simulated data, and compare the outcome to the results of the conventional approaches for validation. Thereafter we illustrate our method using Dutch breeding bird data. Finally, we show how the method can be used to test for change-points in the MSI and trend differences between MSIs and some additional possibilities for trend assessment.

2. Methods

2.1. Calculating MSIs and confidence intervals by Monte Carlo simulation

The starting point of the Monte Carlo (MC) method is a data set with species indices and standard errors, for instance calculated with the TRIM software (Pannekoek and Van Strien, 2005). The index value in some pre-defined base year is set to 100 with standard error zero (step 1 in Fig. 1). The indices in the other years are expressed as percentage of the base year and their standard errors are a function of the variance in the specific year and the base year. Our method assumes that the standard errors are adjusted for the effect of serial correlation between years, which is the standard approach in most monitoring programmes. The indices are approximately log-normal distributed (Pannekoek and Van Strien, 2005) and the standard errors are used for MC simulation. Each available yearly index for each species is simulated 1000 times by drawing from a normal distribution N(μ,σ) with μ = the natural logarithm of the index and σ = the standard error of the index on the log scale (step 2). The standard error of the index on the log scale is assessed by the Delta-method (see e.g. Agresti, 1990) as SE(log scale) = SE(index scale)/index. After simulation the same base year (index = 100) is chosen in each simulation for each species and the other years are expressed as a percentage of the base year (step 3 and 4; for the imputation of missing indices, see below). The mean and standard error of the 1000 MSIs in each year are calculated and back-transformed to the index scale (step 5). The arbitrarily chosen number of 1000 simulations is a trade-off between computational efficiency and accuracy, to insure consistency in estimates across runs. This number could be increased if large variability in the results is observed between different runs.

2.1.1. Missing data

A complication in the procedure described in Section 2.1 arises if some species have missing indices. In practice these missing values will often occur at the beginning or end of the time series (due to differences in monitoring schemes between species). These missing indices must be imputed in order to set the same base year for each species, which is necessary to calculate geometric mean indices. We apply chain indexing (Crawford, 1991) to impute missing species indices, using the relative year-to-year population development in species without missing values (step 3 in Fig. 1). Thus, if all species without missing data show a mean increase of, say, 10% from year t to t + 1, this percentage is used for imputing the missing data points in species with missing data for year t + 1. Note that in each MC simulation different imputed values will be generated. After imputation we proceed with the common procedure to calculate MSIs and standard errors. These standard errors for years with missing species indices do not include the uncertainty caused by imputation.

2.1.2. Handling extreme cases

Using the geometric mean in biodiversity indicators has many advantages (Buckland et al., 2005, 2011; Van Strien et al., 2012), but the downside is that it makes such indicators oversensitive to strongly fluctuating, eruptive, strongly increasing or strongly decreasing species. For such species, index values may show extreme yearly changes or may become extremely large, zero, or close to zero. Especially small indices may have strong and unwanted (as they usually represent very low population numbers) effects on the MSI.

Zero values of indices need special treatment anyhow, as the logarithm of zero is undefined. Often an arbitrary small amount (e.g. 0.1 or 1) is added to zero indices before log transformation. The effect on the