# SEDAR 65 - AW03: Reconciling indices of relative abundance of the Atlantic blacktip shark (*Carcharhinus limbatus*)

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**Reconciling indices of relative abundance of the Atlantic blacktip shark (*Carcharhinus limbatus*)**

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## Introduction

Trends in relative abundance generated from fisheries-independent and -dependent data are important inputs to stock assessments, as they are intended to represent an unbiased estimate of the underlying abundance pattern of a stock (Francis 2011). This representation is based on the assumption that relative abundance indices are proportional to total abundance. However, for species that are distributed over large spatial scales or that exhibit long range migrations, comprehensive population-wide relative abundance data are rarely available. As a result, it is sometimes necessary to rely on several independent data sources derived from spatially distinct sampling programs to estimate the patterns of abundance of widely distributed or highly migratory species. Operationally, multiple time-series of relative abundance are frequently included in a single stock assessment model, under the assumption that each provides representative information about the underlying abundance of the stock (Conn 2010, Cortés et al. 2015).

Many of the coastal shark species that inhabit the southeast Atlantic are geographically widespread and display large-scale seasonal migrations. Accordingly, collection of relative abundance data across spatial scales that match the home range of sharks is logistically challenging and not necessarily of high priority given their low economic impact when compared to species that support high value fisheries (Stevens et al. 2000). The development of relative abundance indices for sharks is therefore constrained to localized data collection programs that sample spatial ranges that are often much smaller than the actual distributions of target species. For the southeast Atlantic, there are several such data collection programs and it is not uncommon for the resulting indices of relative abundance to show conflicting trends over time.

In past stock assessments of coastal sharks in the southeast Atlantic, efforts have been directed at applying statistical techniques to reconcile contrasting patterns in relative abundance indices. In the previous sandbar shark assessment (SEDAR 2011), a hierarchical index compilation approach (Conn 2010) was used to develop a single time-series of relative abundance from the existing, disparate time-series derived from the localized sampling programs. The idea was to synthesize the information contained in the collection of relative abundance indices (11 total for sandbar shark, *Carcharhinus plumbeus*) into a single composite time-series that presumably reflected the trend in abundance at a broader spatial scale. Here, we build on that philosophy by introducing an alternative approach for the integration of multiple time-series, namely dynamic factor analysis (DFA). DFA is a multivariate dimension reduction technique designed to detect common, latent trends from a collection of time-series. This approach can accommodate short, non-stationary time-series like those commonly encountered in ecological data, input time-series with missing data, and covariation between time-series (Zuur et al. 2003a, 2003b, Holmes et al. 2020). Recently, DFA was used to reconcile conflicting indices of relative abundance for seven coastal shark species along the east coast of the United States (Peterson et al. 2017).

## Methods

*Dynamic Factor Analysis*

The general form of a DFA model can be written as follows (Zuur et al. 2003a):

$$\boldsymbol{y}_t = \boldsymbol{\Gamma}\boldsymbol{\alpha}_t + \boldsymbol{\varepsilon}_t, \text{ where } \boldsymbol{\varepsilon}_t \sim MVN(0, \boldsymbol{R})$$
$$\boldsymbol{\alpha}_t = \boldsymbol{\alpha}_{t-1} + \boldsymbol{\eta}_t, \text{ where } \boldsymbol{\eta}_t \sim MVN(0, \boldsymbol{Q})$$

where $\boldsymbol{y}_t$ is the vector (*n* x 1) of estimated z-scored index values from all time-series of relative abundance in year *t*, $\boldsymbol{\alpha}_t$ is the vector (*m* x 1) of common trends (*m* < *n*), $\boldsymbol{\Gamma}$ is the matrix (*n* x *m*) of loadings on the trends which indicates the strength of each time-series in determining the resulting trend, and $\boldsymbol{R}$ and $\boldsymbol{Q}$ denote the variance-covariance matrices associated with the observation error vector $\boldsymbol{\varepsilon}_t$ (*n* x1) and process error vector $\boldsymbol{\eta}_t$ (*m* x 1), respectively. Both observation and process error terms assume a multivariate normal distribution. To ensure that the model is identifiable, $\boldsymbol{Q}$ is set to equal to the identity matrix while $\boldsymbol{R}$ is free to take on various forms. All factor loadings, common trends, and fitted values are unitless.

Application of DFA to time-series of relative abundance requires some care to preserve the underlying error structure and the relative scale of the survey indices. Accordingly, the following analytical approach was adopted: (1) all time-series of relative abundance were log-transformed, thereby normalizing the time-series error, (2) each time-series was centered and demeaned by subtracting and dividing each by its mean, (3) the global standard deviation (*GSD*) was calculated for all relative abundance time-series after being log-transformed and demeaned, (4) each time-series was then divided by the *GSD*, (5) the DFA model was fitted, (6) the resulting DFA-predicted common trend was then multiplied by the *GSD* and back-transformed. Since the stock assessment model relies heavily on trend rather than magnitude of relative abundance indices, bias correcting will have little impact. However, standard errors estimated by the DFA model for the annual indices were multiplied by the *GSD* to preserve scale of uncertainty relative to the trend.

The above approach does not work well in situations where the log-transformed relative abundance mean was close to zero or negative, because the second step would essentially involve dividing by zero or a negative value, respectively. This was the case for a few of the Atlantic blacktip shark time-series of relative abundance. Simulation analyses have also shown that DFA model fitting is fairly robust when the standard deviation of each time-series resulting from step four are approximately one (Peterson et al. in prep). Accordingly, the Atlantic blacktip time-series of relative abundance were first multiplied by a survey-specific constant, $c$, to ensure that the resulting time-series approximately achieved these two general criteria. Multiplying indices by a constant is comparable to redefining effort such that the scale of the index changes. Best practices suggest that time-series be z-scored prior to DFA model fitting (Holmes et al. 2020), so in effect, the above analytical approach was developed in the spirit of maintaining consistency with that recommendation.

The underlying assumptions of a DFA model are equivalent to those of a linear regression, which include normality, independence, and homogeneity of residuals (Zuur et al. 2003b). Model validation was therefore based on standard diagnostic tools (QQ plots, analysis of residuals). Additionally, 'fit ratio' statistics were calculated as $\Sigma_t y_{it}^2 / \Sigma_t \varepsilon_{it}^2$, where $i$ denotes an individual time-series. High fit ratios (i.e., $\gtrsim 0.6$) suggest that the DFA model poorly fits the time series, or a few years in the time series (Zuur et al. 2003b).

For application to Atlantic blacktip shark, two analyses were performed, where the first involved analyzing time-series of relative abundance indices for age-0 individuals (2001-2018) derived from the COASTSPAN Longline Survey, the COASTSPAN Long Gillnet Survey, and the COASTSPAN Short Gillnet Survey, and the second involved analyzing time-series of relative abundance for all ages (1990-2018) derived from the shark bottom longline fishery, the shark research fishery, the Virginia Shark Monitoring and Assessment Program (VASMAP), the Northeast Fisheries Science Center (NEFSC), the Southeast Area Monitoring and Assessment Program (SEAMAP), and the South Carolina Red Drum Survey. Within both the age-0 and all ages analysis, a single common trend was estimated and each time-series was assumed to be independent with a unique value of uncertainty. Therefore, that $\boldsymbol{R}$ matrix of the DFA models each assumed a structure with the mean of the time-series-specific coefficients of variation (CVs) along the diagonal and zeros elsewhere. CVs were chosen over estimated variances so that the magnitude of uncertainty across time-series would be similar. DFA models were fitted using the state-space multivariate autoregressive modelling package 'MARSS' in R (Holmes et al. 2020) and all uncertainty was reported as 95% confidence intervals.

## Results/Discussion

The raw time-series of relative abundance showed conflicting patterns over years for both the age-0 and all-ages combined, which provided motivation for reconciliation prior to stock assessment modeling (Figure 1). For the age-0 analysis, the constants chosen for rescaling and ensuring that the standard deviations of the time-series following step four ($GSD$ = 0.29) were approximately 1.0 were 2, 30, and 13 for COASTSPAN Longline, COASTSPAN Long Gillnet, and

COASTSPAN Short surveys, respectively. The DFA model successfully converged and yielded a common trend that generally increased from 2001-2010, but decreased thereafter (Figure 2a). Factor loadings on the common trend were positive and statistically significant for the COASTPAN Longline (CI: 0.46, 1.46) and Long Gillnet (CI: 0.10, 0.73) surveys, with the former showing the strongest adherence (Figure 2b). The COASTSPAN Short Gillnet showed a weakly negative and non-significant (CI: -0.44, 0.18) loading on the common trend. Fit of the common trend to the standardized time-series of relative abundance from the COASTPAN Longline Survey was very good (fit ratio = 0.14), while fits to the other two standardized time-series were poor (fit ratios = 0.77, 0.98, respectively; Figure 2c). Thus, the COASTSPAN Longline Survey time-series appears to drive the estimated common trend in age-0 Atlantic blacktip relative abundance, likely due to the mean CV of that survey being the lowest amongst the time-series. The pattern of the back-transformed time-series did not differ substantially from the common trend other than the intended shift in scale (Figure 3). Uncertainty in the back-transformed trend was greatest in the early years due to only one contributing relative abundance time-series but reasonable thereafter.

For the all-ages analysis, the constants of 0.13, 0.02, 90, 800, 1.25, and 3.8 were selected for the shark bottom longline fishery, the shark research fishery, VASMAP, NEFSC, SEAMAP, and South Carolina Red Drum Survey, respectively, to rescale and bring the standard deviations of the time-series close to one following step four ($GSD$ = 0.61). The fitted DFA model converged and provided a common trend that was variable but generally increasing across years (Figure 4a). Factor loadings were positive and statistically significant for the bottom longline fishery (CI: 0.11, 0.72), the shark research fishery (CI: 0.03, 0.62), and SEAMAP (CI: 0.27, 1.08; Figure 4b). Loadings were also positive but non-significant for VASMAP (CI: -0.034, 0.32) and NEFSC (CI: -0.029, 0.64). The South Carolina Red Drum Survey factor loading was negative but not statistically significant (CI: -0.61, 0.029). Although the respective factor loadings for SEAMAP, the bottom longline fishery, and the shark research fishery were highest in magnitude, fits of the common trend to those time-series were marginal (Figure 4c). For SEAMAP and the research fishery, the fact that these time-series did not span the full years analyzed likely played a role in the lack of fit to the standardized data. Fits of the common trend to the NEFSC (fit ratio = 0.83), South Carolina Red Drum (fit ratio = 0.79), and shark research fishery (fit ratio = 0.84) standardized data were similarly poor, and each of these surveys also had several years of missing index values (Figure 5). The fit of the common trend to the VASMAP standardized data was the worst (fit ratio = 0.95). In general, the SEAMAP (fit ratio = 0.29) and bottom longline fishery (fit ratio = 0.56) time-series drove the common trend. The back-transformed relative abundance time-series differed slightly from the common trend but the generally increasing pattern and high/low years were preserved. Precision of the back-transformed common trend was low in the early years when few time-series contributed information, but more reasonable thereafter.

## Acknowledgements
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fishery, the shark research fishery, VASMAP, NEFSC, SEAMAP, and South Carolina Red Drum Survey.

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## Figures

Figure 1. Raw time-series of indices of relative abundance for (a) age-0 Atlantic blacktip shark, 2001-2018, and (b) all-ages combined, 1990-2018. Abbreviations: LL – COASTSPAN Longline Survey, GNLong – COASTSPAN Long Gillnet Survey, GNShort – COASTSPAN Short Gillnet Survey, BottomLL – bottom longline fishery, Research – shark research fishery, and RedDrum – South Caroline Red Drum Survey; see text for all others.

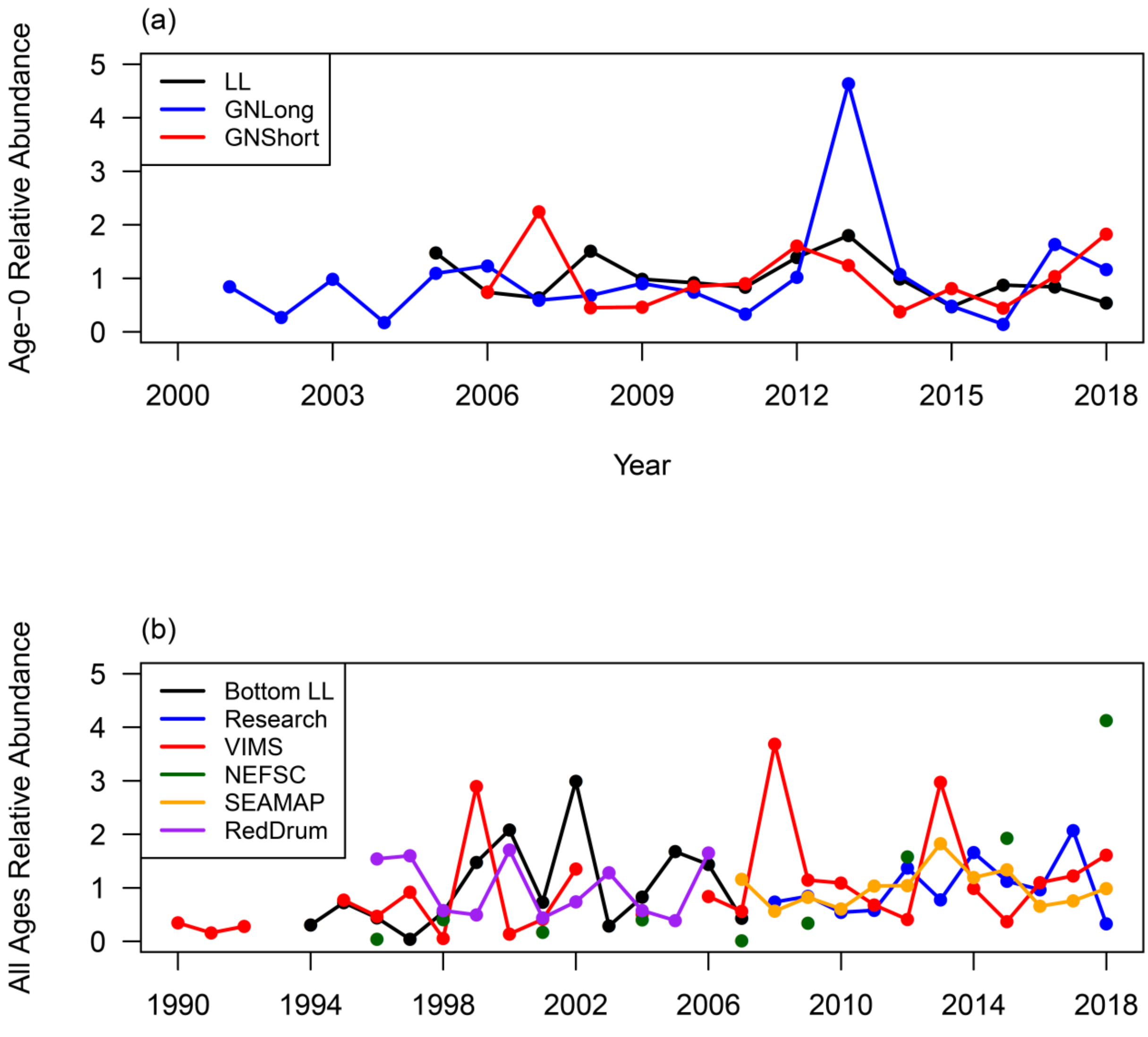

Figure 2. Results of the DFA model fitted to age-0 Atlantic blacktip shark time-series of relative abundance showing (a) the common trend (solid line) and 95% CI (dashed lines), (b) factor loadings; values greater than 0.2 (horizontal dashed line) identify time-series that have a relatively strong influence on the common trend, and (c) fits to the time-series of relative abundance. Abbreviations: LL – COASTSPAN Longline Survey, GNLong – COASTSPAN Long Gillnet Survey, GNShort – COASTSPAN Short Gillnet Survey.

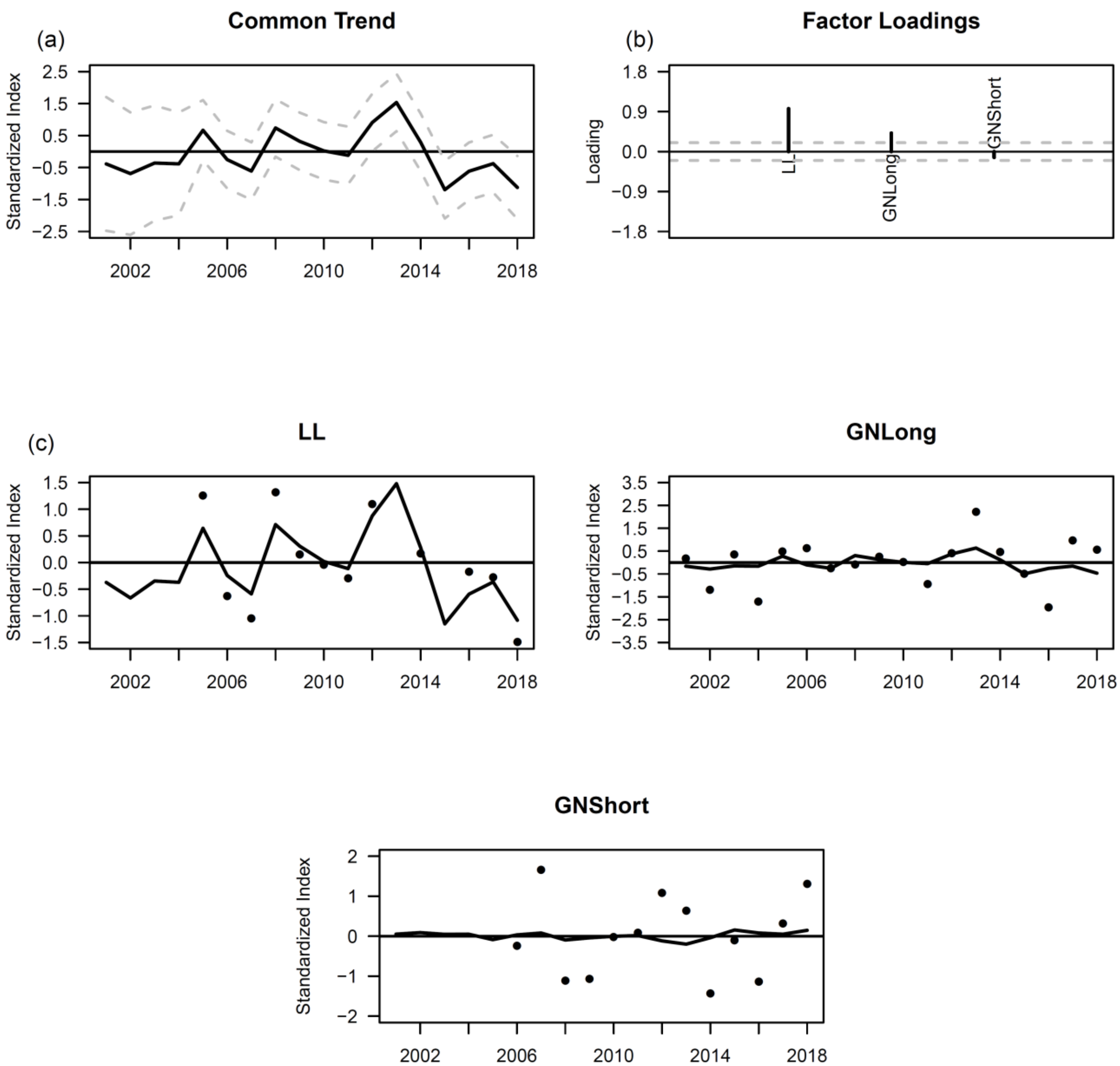

Figure 3. Back-transformed common trend resulting from the DFA model fitted to the age-0 Atlantic blacktip shark time-series of relative abundance. The horizontal line denotes the time-series mean.

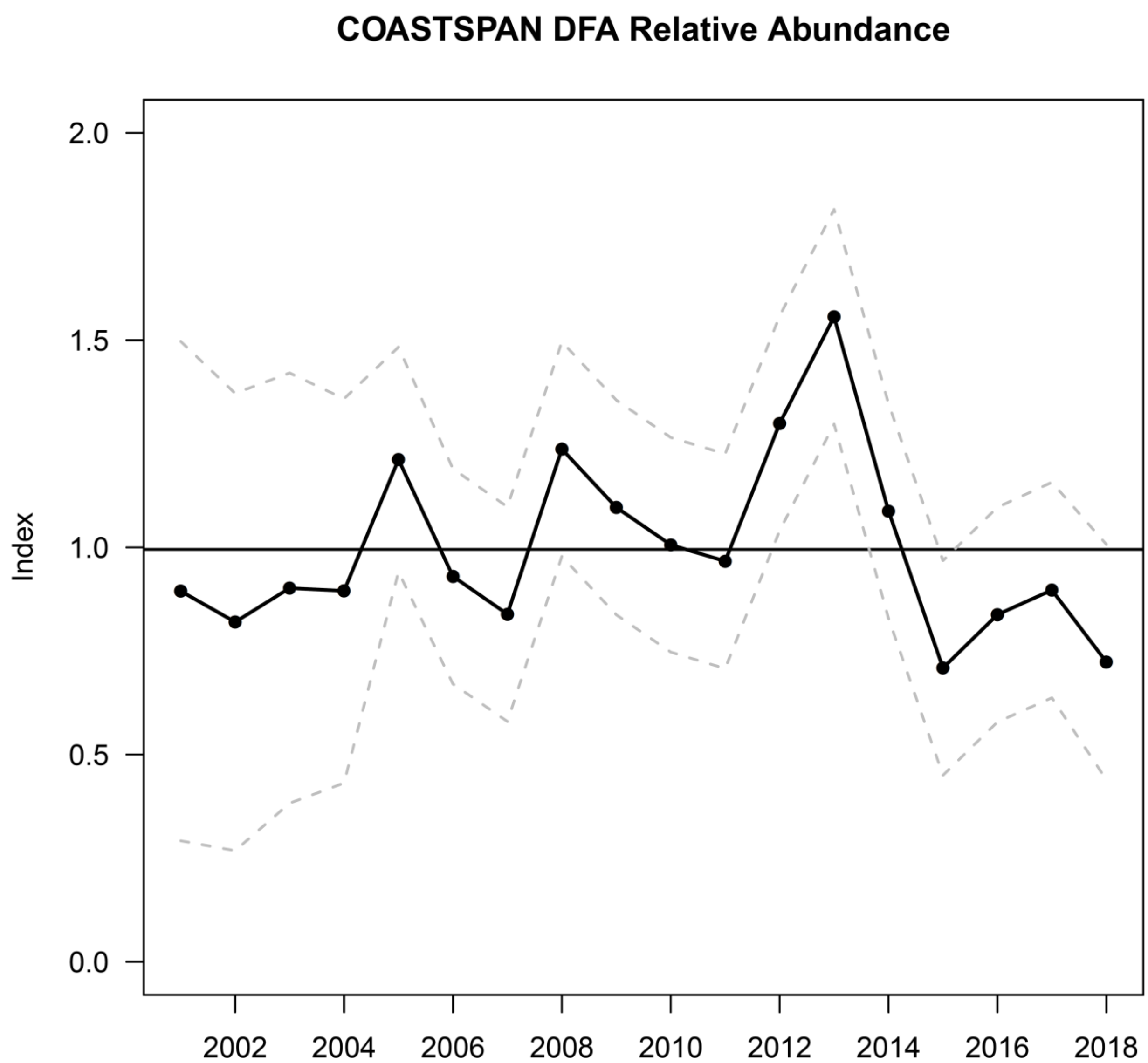

Figure 4. Results of the DFA model fitted to time-series of relative abundance for all ages of Atlantic blacktip shark combined showing (a) the common trend (solid line) and 95% CI (dashed lines), (b) factor loadings; values greater than 0.2 (horizontal dashed line) identify time-series that have a relatively strong influence on the common trend, and (c) fits to the time-series of relative abundance. Abbreviations: BottomLL – bottom longline fishery, Research – shark research fishery, and RedDrum – South Caroline Red Drum Survey; see text for all others.

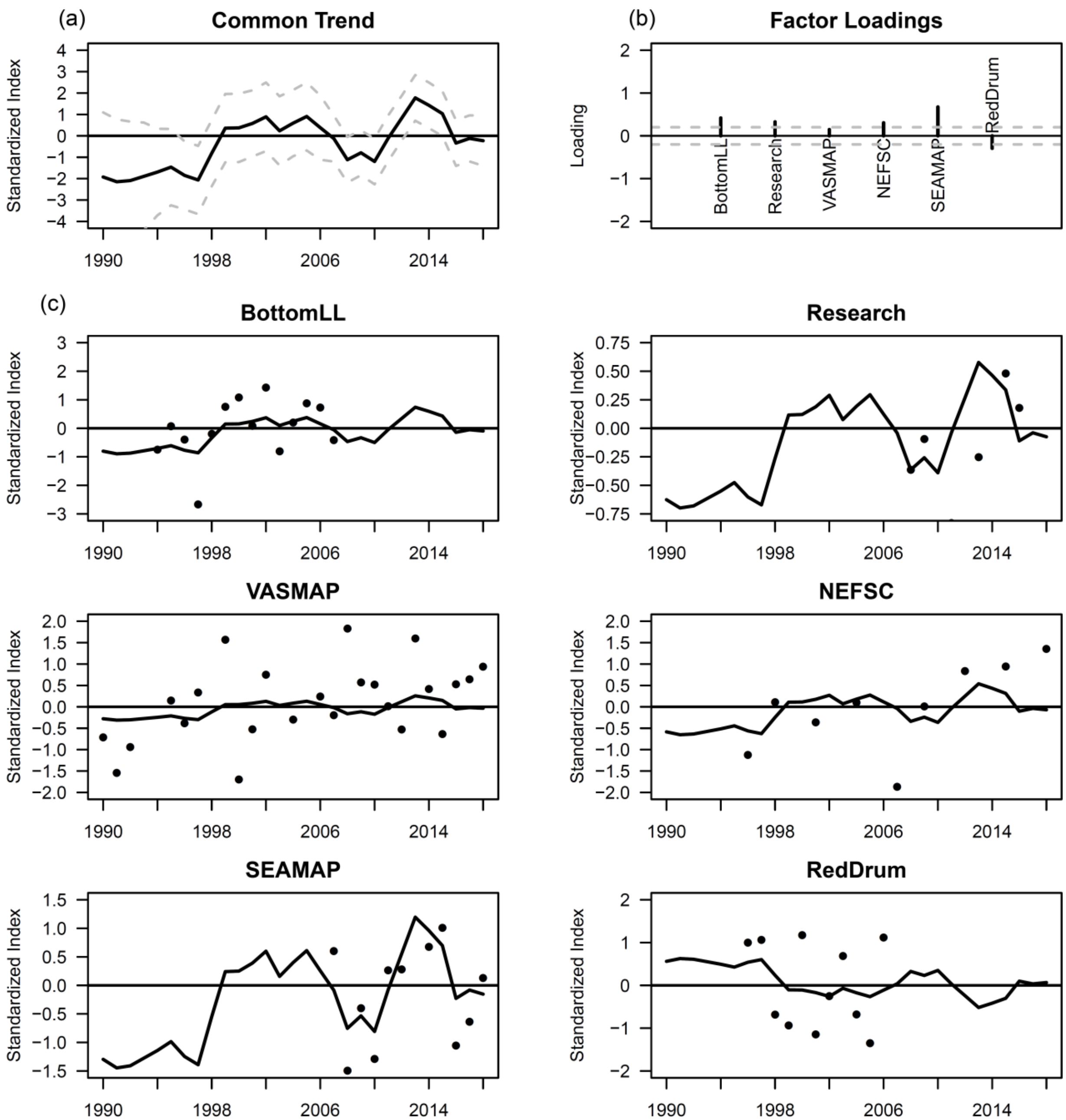

Figure 5. Back-transformed common trend resulting from the DFA model fitted to time-series of relative abundance for all ages of Atlantic blacktip shark combined. The horizontal line denotes the time-series mean.