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11 Full title of paper

12   Preliminary recovery of coastal sharks in the southeast U.S.

13 Title alternatives

14   Broad-scale trends in abundance of coastal sharks in the southeast U.S.

15   Coast-wide indices show recovery of coastal sharks in the southeast U.S.

16

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38   Suggested running title: Atlantic coastal shark recovery

Abstract

40   Relative abundance of many shark species in the Atlantic is assessed by compiling data from
41   several independently conducted, but somewhat spatially limited surveys. Although these localized
42   surveys annually sample the same populations, resulting trends in yearly indices often conflict with
43   one another, thereby hindering interpretation of abundance patterns at broad spatial scales. We
44   used delta-lognormal generalized linear models (GLMs) to generate indices of abundance for seven
45   Atlantic coastal shark species from six fishery-independent surveys along the U.S. east coast and
46   Gulf of Mexico from 1975 to 2014. These indices were further analysed using dynamic factor
47   analysis (DFA) to produce simplified, broad-scale common trends in relative abundance over the
48   entire sampled distribution. Effects of drivers including the North Atlantic Oscillation index, the
49   Atlantic Multidecadal Oscillation index, annually averaged sea surface temperature, and species
50   landings were evaluated within the DFA model. The two decadal oscillations and species landings
51   were shown to affect shark distribution along southeast U.S. coast. Estimated common trends of
52   relative abundance for all large coastal shark species showed similar decreasing patterns into the
53   early 1990s, periods of sustained low index values thereafter, and recent indications of recovery.
54   Small coastal shark species exhibited more regional variability in their estimated common trends,
55   such that two common trends were required to adequately describe patterns in relative abundance
56   throughout the Gulf of Mexico and Atlantic. Overall, all species' (except the Gulf of Mexico blacktip
57   shark) time series concluded with an increasing trend, suggestive of initial recovery from past
58   exploitation.

59

60 **Key words:** Coastal sharks; data conflict; dynamic factor analysis; index of abundance; generalized
61 linear models
62
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Introduction

While it is generally agreed upon within the scientific community that shark stocks rapidly declined in abundance along the U.S. east coast beginning in the mid-1970s through the early 1990s (Stevens *et al.* 2000; Cortés *et al.* 2002; Dulvy *et al.* 2014; Grubbs *et al.* 2016), the extent of that decline has been contentiously debated in the scientific literature with varyingly pessimistic outlooks. Studies quantifying population declines have largely been restricted to modelling effects in a localized area from a single fishery-independent survey (e.g., Musick *et al.* 1993; Musick *et al.* 2000; Myers *et al.* 2007) or at a broader scale using fishery-dependent data (e.g., Baum *et al.* 2003; Myers and Worm 2003; Baum and Myers 2004; Baum *et al.* 2005; Burgess *et al.* 2005a; b; Myers *et al.* 2007; Baum and Blanchard 2010). In particular, substantial declines as reported by Baum *et al.* (2003) and Baum and Myers (2004) were rebutted by Burgess *et al.* (2005a), resulting in additional exchanges (Baum *et al.* 2005; Burgess *et al.* 2005b; see Field *et al.* 2009 for more extensive review). These declines may hold economic and ecosystem-wide implications as effects of altered apex predator abundance propagate down the food web via direct and indirect trophic cascades, where sharks likely facilitate natural selection of their prey (Stevens *et al.* 2000; Scheffer *et al.* 2005; Baum and Worm 2009; Ferretti *et al.* 2010; Heupel *et al.* 2014).

Shark exploitation along the southeast coast of the U.S. began in the mid-1970s coincident with declining stock abundances of other commercially important species, and since sharks were deemed an underutilized natural resource at that time, fishers were encouraged to focus on sharks for commercial harvest (Musick *et al.* 1993; McCandless *et al.* 2014). Simultaneously, directed recreational shark fisheries rapidly developed in response to public excitement stemming from the release of the movie "Jaws" in 1975 (Musick *et al.* 1993; Cortés *et al.* 2006). Yet, many sharks are inherently susceptible to fishing pressure due to their K-selected life history strategy (Musick *et al.* 2000; Stevens *et al.* 2000; Au *et al.* 2015). Large-bodied, coastal shark species were likely most affected by the development of targeted fisheries due to their high meat content, large fin sizes, and close proximity to land (Dulvy *et al.* 2014). Contrary to larger species, small coastal sharks in the northwest Atlantic, which generally are not considered apex predators, have experienced less dramatic declines in abundance (SEDAR 2007). These smaller species have comparably higher intrinsic population growth rates, and consequently are less susceptible to fishing pressure (Au *et al.* 2015).

As a result of declines in large coastal shark stocks within the U.S., a shark fishery management plan (FMP) was established by the National Marine Fishery Service (NMFS) in 1993, which initiated the enactment of several commercial and recreational regulations in federal Atlantic

120   waters (SEDAR 2011). Prior to the implementation of management measures, shark population
121   dynamics were not the focus of extensive scientific investigation. The FMP noted a lack of species-
122   specific data required to conduct individual stock assessments, which stimulated numerous life
123   history studies of shark stocks within the southeast U.S., and several state and federal agencies
124   began collecting relative abundance information either through directed surveys or as bycatch of
125   existing surveys (NMFS 1993). However, due to their sex- and size-specific migratory patterns and
126   the expansive spatial distributions of Atlantic coastal sharks, developing stock-wide
127   characterizations of relative abundance is challenging (Kohler *et al.* 1998; Castro 2011;
128   Simpfendorfer and Heupel 2012). At present, inferences about shark abundance in the Atlantic are
129   largely based on catch-per-unit-effort (CPUE) data obtained from several relatively spatially limited
130   surveys. When multiple independent surveys each sample a small or incomplete portion of a stock's
131   migratory range, it is not uncommon for the resulting trends in CPUE to be in conflict, which creates
132   uncertainty about true population trends (SEDAR 2013). Thus, developing representative
133   characterizations of stock-wide dynamics and patterns in relative abundance for sharks in the
134   Atlantic involves reconciling discrete, and often contradictory, fragments of information.

135   The objectives of the study were two-fold: i) develop simplified broad-scale trends of
136   relative abundance for seven Atlantic shark species by integrating data from multiple fishery-
137   independent survey programs performed at differing spatial scales, and ii) investigate the effects of
138   hypothesized drivers (climatic, environmental, anthropogenic) on resultant broad-scale temporal
139   patterns of relative abundance. We acquired raw data from six fishery-independent surveys and
140   used those data to generate indices of relative abundance for seven species, including four large
141   coastal species (LCS; sandbar shark, *Carcharhinus plumbeus*, Carcharhinidae; blacktip shark, *C.*
142   *limbatus*, Carcharhinidae; spinner shark, *C. brevipinna*, Carcharhinidae; tiger shark, *Galeocerdo*
143   *cuvier*, Carcharhinidae) and three small coastal sharks (SCS; Atlantic sharpnose shark,
144   *Rhizoprionodon terraenovae*, Carcharhinidae; blacknose shark, *C. acronotus*, Carcharhinidae;
145   bonnethead, *Sphyrna tiburo*, Sphyrnidae). Large and small coastal shark designations distinguish
146   management units along the Atlantic coast of the U.S. as defined by NMFS (1993). The relative
147   abundance indices were jointly analysed for underlying common trends in abundance using
148   dynamic factor analysis (DFA), a multivariate dimension reduction approach for time series. We
149   subsequently examined the effects that broad-scale environmental and anthropogenic drivers had
150   on these species-specific relative abundances.

Methods

151 **Methods**

152 *Data sources*

153   Catch and effort data from six fishery independent shark surveys ranging from 1975-2014
154 were the basis for this study: the Virginia Institute of Marine Science Longline (VIMS LL), SouthEast
155 Area Monitoring and Assessment Program-South Atlantic Coastal Trawl Survey (SEAMAP-SA
156 Trawl), South Carolina Coastal Longline Survey (SC LL), Georgia Red Drum Longline Survey (GA LL),
157 Southeast Fisheries Science Centre Longline Survey (SEFSC LL), Gulf of Mexico Shark Pupping and
158 Nursery Gillnet Survey (GULFSPAN GN; Fig. 1; Table S1). Data for the SEAMAP-SA Trawl, SC LL, and
159 GA LL can be accessed from www.seamap.org (SEAMAP-SA Data Management Work Group). A
160 minimum of three independent survey-based indices of abundance were required for a given
161 species to be considered for analysis (with the exception of the tiger shark). Data from seven shark
162 species were analysed (Table S2).

163 *Indices of abundance*

164   Generalized linear models (GLMs; McCullaugh and Nelder 1989) were used to standardize
165 species-specific CPUE data from each survey program and provide estimated annual indices of
166 relative abundance. Preliminary explorations of each survey dataset revealed high frequencies of
167 zero observations, which were expected given the fishery-independent nature of the surveys and
168 low overall abundance of the focal species. Consequently, delta-lognormal GLMs were used to
169 generate species-specific relative abundance indices from each survey (Lo *et al.* 1992; Maunder and
170 Punt 2004; Cortés *et al.* 2006), where the survey observations were defined as number of sharks
171 captured per hook-hours, per net area-hours, or per area swept for longline, gillnet, and trawl
172 gears, respectively. For the purposes of the current study, we assumed that gear selectivity was
173 principally constant over time.

174   Delta-lognormal models contain two components (Pennington 1983). The binomial
175 submodel is fitted to presence/absence data, where presence is defined as sampling events in
176 which at least one target species was captured, and estimates the probability of encountering the
177 target species. The lognormal submodel, fitted to the log-transformed nonzero observations, is used
178 to estimate the mean CPUE. The general form of a delta-lognormal GLM is:

$$logit(\pmb{\pi_B}) = \pmb{X_B}\pmb{\beta_B} + \pmb{\varepsilon_B}, \ \ \text{where } \pmb{\varepsilon_B} \sim N(0, \sigma_B^2)$$

179 $$\pmb{\mu_{CPUE}} = \pmb{X_{CPUE}}\pmb{\beta_{CPUE}} + \pmb{\varepsilon_{CPUE}}, \ \ \text{where } \pmb{\varepsilon_{CPUE}} \sim N(0, \sigma_{CPUE}^2) \tag{1}$$

180 where $\pmb{\pi_B}$ represents the probability that each observation (i.e., sampling event) is non-zero, $\pmb{\mu_{CPUE}}$ is
181 the log-transformed CPUE, and in both submodels, $\pmb{X}$ is the design matrix, $\pmb{\beta}$ is the vector of

182   estimated parameters, and $\boldsymbol{\varepsilon}$ is the associated observation error. Predicted indices of relative
183   abundance were generated using estimated marginal means (Searle *et al.* 1980), and back
184   transformed bias correction followed Lo *et al.* (1992). The resulting predictions over years from
185   both submodels were multiplied to generate a final annual index of relative abundance.
186   Uncertainty estimates for the annual indices were generated from 1000 nonparametric
187   bootstrapped samples (Efron and Tibshirani 1993). All analyses of survey data were performed
188   with the software package R (version 3.1.1, R Core Development Team 2014).

189   Akaike's Information Criterion (AIC, Akaike 1973, Burnham and Anderson 2002) was used
190   to discriminate among model parameterizations containing different combinations of covariates.
191   The covariates examined varied by survey (Table S1), while year was included in all models to
192   ensure estimation of annual abundance indices. Year, month/season, and station/area were treated
193   as categorical variables, and levels of those categorical variables were excluded from analyses if the
194   species of interest was not present during at least two sampling events. Latitude, longitude, and
195   depth were standardized and treated as continuous variables. Scatter plot matrices and variance
196   inflation factors (VIFs) were used to assess correlation and collinearity of covariates. Covariates
197   with correlation coefficient of large magnitudes ($\gtrsim 0.7$) or that produced large VIFs (> 10) were not
198   mutually included in any model. Graphical residual analysis, deviance explained, and dispersion
199   analysis were used to assess model fit. Resulting indices of abundance were standardized (Z-
200   scored) prior to implementation into the dynamic factor analysis model.

201 *Dynamic factor analysis*

202   Dynamic factor analysis is a multivariate dimension reduction technique designed for
203   relatively short, non-stationary time series data. The approach involves fitting a specialized,
204   multivariate, autoregressive state-space model to identify a set of underlying trends that explain
205   temporal variation in a collection of short time series (Zuur *et al.* 2003a; b; Holmes *et al.* 2014). The
206   general form of a DFA model can be written:

207         $\boldsymbol{y}_t = \boldsymbol{\Gamma}\boldsymbol{\alpha}_t + \boldsymbol{D}\boldsymbol{x}_t + \boldsymbol{\varepsilon}_t$, where $\boldsymbol{\varepsilon_t} \sim MVN(0, \boldsymbol{H})$

208         $\boldsymbol{\alpha}_t = \boldsymbol{\alpha}_{t-1} + \boldsymbol{\eta}_t$, where $\boldsymbol{\eta_t} \sim MVN(0, \boldsymbol{Q})$ (2)

209   where the top equation represents the observation component, and the second equation represents
210   the process or state component. The ($n \times 1$) vector $\boldsymbol{y}_t$ is comprised of abundance indices at time t, $\boldsymbol{\alpha}_t$
211   is the vector ($m \times 1$) of common trends ($m < n$) that are modelled as stochastic random walks, $\boldsymbol{\Gamma}$ is the
212   matrix ($n \times m$) of estimated factor loadings on the common trend(s), $\boldsymbol{x}_t$ is the vector ($k \times 1$) of drivers,
213     $\boldsymbol{D}$ holds the corresponding coefficients ($n \times k$), and $\boldsymbol{H}$ and $\boldsymbol{Q}$ denote the variance-covariance matrices
214   associated with the observation error vector $\boldsymbol{\varepsilon}_t$ ($n \times 1$) and process error vector $\boldsymbol{\eta}_t$ ($m \times 1$),

215 respectively (Zuur *et al.* 2003a; b; Holmes *et al.* 2014). The process component of DFA fits
216 autocorrelated common trends to accommodate the time series nature of the indices and resulting
217 trends (Stachura *et al.* 2014). Factor loadings (elements of the Γ matrix) indicate the strength of the
218 influence of each survey index on the resulting common trend. Values higher in magnitude (≥ 0.2)
219 denote a stronger effect of the given survey on the corresponding common trend. Since the indices
220 were Z-scored, the resulting factor loadings, common trends, and fitted values were unitless (Zuur
221 *et al.* 2003b). Significance of factor loadings and drivers were defined as 95% confidence intervals
222 (CIs) that did not overlap zero.

223   To ensure that the model was identifiable, Q was set to the identity matrix (I) and H, which
224 specifies the variance-covariance structure between the n time series, was allowed to take on four
225 forms: diagonal with equal variance and zero covariance, diagonal with unequal variance and zero
226 covariance, nondiagonal with equal variance and equal covariance, and unconstrained with unique
227 variances and covariances (Holmes *et al.* 2014). Model implementation occurred using the state-
228 space multivariate autoregressive modelling package 'MARSS' (Holmes *et al.* 2013) in R (version
229 3.1.1).

230   Models were fitted in two-steps (Supplement 1). First, all combinations of one, two, or three
231 common trends and the four covariance matrix structures were explored in the absence of drivers,
232 and corrected Akaike's Information Criterion (AICc) for low sample sizes was used for model
233 selection (Holmes *et al.* 2014), along with graphical evaluation. An additional quantitative measure
234 of model fit, which was calculated as the sum of the squared residuals (r) of the fitted trend divided
235 by the sum of the squared observations ($\sum r_t^2 / \sum \hat{y}_t^2$) for each survey, was also used to compare
236 models. Lower quantities (defined as $\lesssim 0.6$) were interpreted as indicative of better model fit, while
237 higher values indicated that all or several years were poorly estimated by the resulting fitted trend
238 (Zuur *et al.* 2003b). For comparative purposes, these values were averaged for all surveys of a given
239 species. Second, the effect of broad-scale drivers were investigated in the most supported model
240 from the first step. The mean fit value, combined with AICc and graphical analyses that assessed
241 agreement between the fitted trend and raw indices of abundance, were collectively used to select
242 the most parsimonious model that best described the indices of relative abundance.

243   Four drivers were examined: (1) the North Atlantic Oscillation (NAO) index, (2) the Atlantic
244 Multidecadal Oscillation (AMO) index, (3) global, annually averaged sea surface temperature (SST)
245 between latitudes 24°N and 44°N (data provided by NOAA/OAR/ESRL PSD, Boulder, Colorado, USA,
246 http://www.esrl.noaa.gov/psd/data/climateindices/list/; GISTEMP Team 2016; Fig. 2a), and (4)
247 species landings (provided by E. Cortés, NMFS, Panama City, FL; Fig. 2b). The NAO, which is a

248 measure of pressure difference over the North Atlantic Ocean, and AMO, which encompasses basin-
249 wide sea surface temperature, circulation patterns, and sea level pressure, were selected as
250 environmental drivers because they directly impact climate patterns and have been shown to affect
251 fish survival and ecosystem organization through bottom-up control in the southeast U.S. Atlantic
252 coast and Gulf of Mexico (Stenseth *et al.* 2002 and references therein; Collie et al. 2008; Nye et al.
253 2009; Nye *et al.* 2014; Karnauskas *et al.* 2015). Annually averaged SST was included because
254 several studies have shown that shark movement is influenced by temperature patterns (e.g.,
255 Merson and Pratt 2001; McCandless *et al.* 2005; Castro 2011). Since AMO and SST were highly
256 positively correlated by definition (correlation coefficient = 0.85), they were not mutually included
257 in any DFA model. Lastly, species-specific landings, pooled across the Atlantic and Gulf of Mexico,
258 were included to examine the effect of top-down pressure on species relative abundance. Drivers
259 were limited to broad-scale processes, as the corresponding effect should encompass the spatial
260 range employed by all surveys. Landings were prepared following procedures routinely applied in
261 shark stock assessments (E. Cortés, personal communication). Dynamic factor analysis requires
262 complete time series of drivers, and landings time series did not encompass the temporal span of
263 the index data for the blacktip shark and tiger shark (first five years had no landings data for each
264 species). Hence, hindcasting over missing years was performed by calculating an average catch
265 from the first five years of observed landings data.

266 ## Results

267 *Indices of abundance*

268 Delta-lognormal GLMs provided acceptable fits to raw survey data as determined by
269 graphical residual analysis, variance inflation factors, dispersion analysis, and estimated parameter
270 values and standard errors. Location and month were the covariates that were most frequently
271 included in the most supported GLMs for each species when generating indices of abundance,
272 followed by depth, when available (Table S3). For all species, superimposed standardized indices of
273 relative abundance display obvious data conflict (Fig. 3), such that visual interpretation of broad-
274 scale patterns in species relative abundances is challenging.

275 *Dynamic factor analysis*

276 Time series of relative abundance were well-fitted by the DFA models for all species, with
277 the exception of spinner shark (Tables 1, S4, S5; Figs. S1 and S2). Similarly, either one or two
278 common trends were identified for each species. A diagonal covariance structure was empirically
279 supported for all species, suggesting that no covariance exists between survey indices for the focal

280   species. Furthermore, DFA models were optimally fitted when variances for each survey index
281   within the covariance matrices were assumed to be equal for each species, except for Atlantic
282   sharpnose shark, where a unique variance was estimated for each survey and no covariance was
283   included in the model.

284   The DFA results for the large coastal sharks showed consistent trends in relative abundance
285   across species. For example, the sandbar shark common trend (Fig. 4a) indicated that relative
286   abundance peaked in the early 1980s, decreased until the early 1990s, remained low for several
287   years, and exhibited a modest recovery in the late 2000s. This common trend was well supported
288   by the VIMS LL, SEFSC LL, and GA LL, as indicated by statistically significant factor loadings, with a
289   negative loading by the SC LL (Fig. 4b), such that the SC LL showed a generally decreasing trend
290   from 2007-2014 (Fig. S1). The NAO, which was included in the optimal DFA model for sandbar
291   shark, had a significantly negative effect on the VIMS LL and a positive effect on the GA LL indices of
292   abundance for the sandbar shark (Table S5).

293   The blacktip shark showed a similar common trend to sandbar shark, although the initial
294   recovery began sooner in the time series (Fig. 4c). The trend was significantly and positively driven
295   by the VIMS LL, SEAMAP-SA Trawl, and SEFSC LL surveys, while the GULFSPAN GN and SC LL
296   negatively loaded on the blacktip shark trend (Fig. 4d), suggesting that the latter indices were
297   following an opposing signal of relative abundance as compared to the estimated common trend
298   (Fig. S1). The GULFSPAN GN primarily captured immature blacktip shark, such that the Gulf of
299   Mexico juvenile trend was decreasing. The short SC LL and GA LL indices of relative abundance
300   (2007–2014) showed generally increasing patterns whereas the common trend showed a minimal
301   decline during those years (Fig. S1), explaining the negative factor loadings. The AMO was included
302   in the optimal DFA model for the blacktip shark and had a significantly negative effect on the VIMS
303   LL index of abundance and a positive effect on the GULFSPAN GN and SC LL indices (Table S5).

304   The tiger shark trend also showed a decrease in abundance into the early 1990s, followed
305   by a period of low relative abundance (Fig. 4e). However, in the early 2000s, the relative abundance
306   of tiger shark began to increase much more rapidly than the other large coastal species. Factor
307   loadings indicated that the VIMS LL and SEFSC LL both significantly positively influenced the
308   common trend (Fig. 4f). The optimal DFA model for the tiger shark included the NAO index, which
309   had a significantly negative effect on the SEFSC LL index, and landings, which showed a significantly
310   positive effect on the SEFSC LL index (Table S5).

311   The spinner shark time series was much shorter (Fig. 4g), and raw indices of abundance
312   showed little contrast in relative abundance across years, resulting in low and insignificant factor

313 loadings (Fig. 4h). Nevertheless, the common trend was positively driven by the VIMS LL and
314 negatively driven by the GULFSPAN GN indices of relative abundance (85% CIs excluded zero). The
315 resulting trend reflected an increase of relative abundance from the late-1990s to 2014.

316 The small coastal complex showed more regionally distinctive trends in relative abundance,
317 as all species exhibited two common trends or opposing factor loadings (Table 1; Fig. 5). The first
318 Atlantic sharpnose shark trend showed moderately stable relative abundances until the mid-2000s,
319 followed by a subsequent increase (Fig. 5a). This first trend was primarily driven by the SEFSC LL,
320 which principally samples the Gulf of Mexico. However, it was also significantly driven by sampling
321 off the coast of Virginia by the VIMS LL (Fig. 5b). The secondary trend was largely uninformed prior
322 to the late 1980s, showed a steady increase in abundance into the mid-2000s, and a moderate
323 decline to 2014. This second trend was significantly driven by the SEAMAP-SA Trawl and SC LL,
324 which both sample in the Atlantic.

325 Although the optimal blacknose DFA model produced a single trend that showed a clear
326 decrease in abundance from the mid-1990s into the 2010s (Fig. 5c), the factor loadings indicated
327 opposing trends in relative abundance based on region (Fig. 5d). The common trend was
328 significantly positively influenced by the SEFSC LL and GULFSPAN GN, indicating that the common
329 trend was representative of a decline in blacknose shark abundance within the Gulf of Mexico.
330 Contrarily, the SEAMAP-SA Trawl had a significantly negative factor loading, suggesting that
331 blacknose shark sampled along the Atlantic coast underwent an increase in relative abundance (Fig.
332 S2). The NAO index was included in the optimal blacknose shark model, and had a significantly
333 negative effect on the GULFSPAN GN index and a positive effect on the SC LL index (Table S5).

334 Despite the two common trends estimated for the bonnethead (Fig. 5e), only the primary
335 trend was indicative of the pattern of abundance of bonnethead in the Atlantic. The second common
336 trend was included to better accommodate the increase in SC and GA LL survey indices (Fig. S2),
337 explaining the broad uncertainty prior to 2007. Since the GULFSPAN GN showed low and
338 insignificant factor loadings (Fig. 5f), it is difficult to draw inferences about patterns in relative
339 abundance of bonnethead within Gulf of Mexico.

340 ## Discussion

341 *Indices of abundance*

342 Spatial and temporal covariates were important explanatory variables of local shark
343 relative abundance for all species examined. Considering the broad seasonal migratory patterns of
344 several shark species (Speed 2010 and references therein), it is expected that CPUE of the surveys
345 in this study will change with month/season. Similarly, as sampling areas (or other measures of

346 spatial sampling distribution) represent environmental variability, their importance in explaining
347 CPUE patterns is not surprising since target species will distribute according to preferred habitat
348 types. Additionally, depth also reflects habitat suitability, and when this covariate was available, it
349 too was important in explaining changing CPUE of sampled species. Results from the delta-
350 lognormal GLMs collectively showed that CPUE was variable across space, season, and depth, even
351 within the relatively small areas covered by the surveys. Consequently, obtaining conflicting
352 patterns in indices is likely, which motivates the need for data reconciliation to develop a robust
353 understanding of relative abundance.

354 *Large coastal abundance*

355   The drastic decline in LCS stocks has been extensively debated (i.e. Baum *et al.* 2003; Baum
356 and Myers 2004; Baum *et al.* 2005; Burgess *et al.* 2005a; b; Grubbs *et al.* 2016). Postulated declines
357 of 60-99% relative to virgin conditions have been suggested for several coastal shark species into
358 the 1990s and 2000s (Musick *et al.* 1993; Baum *et al.* 2003; Baum and Myers 2004; SEDAR 2006;
359 Myers *et al.* 2007; SEDAR 2007; Baum and Blanchard 2010; SEDAR 2011; 2012). However, the
360 patterns of relative abundance described in the current study provide a more optimistic outlook
361 and more closely align with results presented by Carlson *et al.* (2012), where spinner shark and
362 tiger shark, among other species, were shown to have increased in abundance by 14% and 3%,
363 respectively, following enactment of the shark FMP. Those results showed preliminary recovery
364 and stabilization of some LCS stocks by 2009 within the commercial bottom longline fishery
365 (Carlson *et al.* 2012).

366   Thus far, studies estimating LCS stock declines have relied on independent and fragmented
367 information, typically only analysing data from a single survey, where changes in regional
368 distribution may be interpreted as changes in abundance. Indices of abundance from disparate
369 surveys frequently result in conflicting information due to high levels of uncertainty and the
370 variable timing of sampling relative to environmentally driven shark migrations (Grubbs 2010).
371 Additionally, complex life cycles, which include size- and sex-specific habitat and movement
372 patterns, result in indices of relative abundance that may only be representative of a portion of the
373 species' life cycle (Kohler *et al.* 1998; Castro 2011; Simpfendorfer and Heupel 2012). For example,
374 sandbar sharks mate within the coastal waters of Florida during June and July (Portnoy *et al.* 2007;
375 Baremore and Hale 2012). A year later, gravid females migrate northward along the Atlantic coast
376 to pup in bays and estuaries during late spring and early summer, after which they migrate back
377 offshore (Grubbs *et al.* 2007; McCandless *et al.* 2005, Baremore and Hale 2012). Neonates remain in
378 these nurseries throughout the summer (McCandless *et al.* 2005; Conrath and Musick 2010), and

379 overwinter off the coast of North Carolina (Grubbs *et al.* 2007; McCandless *et al.* 2005; Conrath and
380 Musick 2008). These juveniles return to their natal nursery for the next five to 16 years (Merson
381 and Pratt 2001; Grubbs *et al.* 2007; McCandless *et al.* 2005), before migrating offshore and into the
382 Gulf of Mexico (Casey *et al.* 1985; Conrath and Musick 2008). Adult male sandbar sharks reside
383 primarily offshore and only move inshore to mate (Casey *et al.* 1985; Portnoy *et al.* 2007; Conrath
384 and Musick 2008).

385   In the current study, CPUE data from several surveys were analysed outside the context of a
386 stock assessment model to reconcile data conflict and provide representative trends of broad-scale
387 relative abundance, where increased abundance suggests preliminary recovery of LCS species. All
388 LCS species followed similar trends in relative abundance, with high levels at the beginning of the
389 time series, followed by a decline until the early 1990s, and signs of recovery in the mid-2000s.
390 Given the low intrinsic population growth rates of many shark species (Au *et al.* 2015), it is
391 reasonable to assume that efficacy of management regulations would not immediately translate
392 into stock recovery (Musick *et al.* 2000). The results of the current study support that reasoning
393 since relative abundance trends of all large coastal species remained depressed following
394 implementation of the 1993 shark FMP. The duration of low relative abundance varied by species
395 however, and relative abundances of those with younger ages-at-maturity (Table S2) showed
396 quicker recoveries than those with older ages at first reproduction.

397   The sandbar shark period of extended low abundance may have also been related to state-
398 wide fisheries targeting young and late juvenile animals, since state and federal management was
399 not formally linked until 2009 (Grubbs 2010). Within Atlantic state waters, sandbar shark utilize
400 large estuaries as nursery areas along the coast (Merson and Pratt 2001; Grubbs *et al.* 2007;
401 McCandless *et al.* 2005), facilitating survival to maturity (Heupel and Hueter 2002; Heupel *et al.*
402 2007). Hence, given the critical role that state waters play in the lifespan of several shark species, it
403 is necessary to consider the synergistic effects of federal and state management regulations.

404   The recent increase in the blacktip shark trend was gradual and showed a great deal of
405 variability, which could be attributed to various management measures, such as the staggered
406 mandatory implementation of bycatch reduction devices (BRDs) within the shrimp trawl fishery
407 (SEDAR 2013; mandated in 1997 in the southeast Atlantic coast, 1998 in the western Gulf of
408 Mexico, and 2004 in the eastern Gulf of Mexico; Scott-Denton *et al.* 2012). Despite surveys sampling
409 two genetically distinct stocks of blacktip shark (Keeney *et al.* 2005), a single common trend was
410 selected to encompass abundance patterns in both the Atlantic and the Gulf of Mexico, potentially
411 indicating that sufficient data were not available within either or both stocks to distinguish

412   alternative relative abundance patterns, or that both stocks were following a similar trend in
413   relative abundance. The tiger shark recovery was extremely large in magnitude, likely reflective of
414   the relatively high fecundity of these sharks, in which females produce an average of 41 pups every
415   two years in the Atlantic (Castro 2011) or three years in the Pacific Ocean (Whitney and Crow
416   2007). While the spinner shark common trend was shorter due to the limited length of each time
417   series included, the modest increase in relative abundance corresponds with that of the other large
418   coastal species, despite larger uncertainty in the resulting estimated trend.

419   *Small coastal abundance*

420   Due to a higher capacity to recover (Au *et al.* 2015), SCS species underwent declines of
421   generally smaller magnitudes than LCS species. Stock assessments have suggested declines of 35-
422   55% relative to virgin abundance for Atlantic sharpnose shark and bonnethead (SEDAR 2007;
423   2013), compared to an estimated 80-85% decline in Atlantic and Gulf of Mexico blacknose shark
424   (SEDAR 2011). In contrast, Myers *et al.* (2007) suggested seemingly exponential increases in
425   mesopredator abundances, particularly Atlantic sharpnose shark, coinciding with declining LCS
426   abundances. In the current study, with the exception of the Gulf of Mexico blacknose shark, relative
427   population declines were minimal and followed by substantial increases that were much smaller in
428   magnitude than those predicted by Myers *et al.* (2007).

429   While the large coastal species typically undergo extensive migrations between the Atlantic
430   Ocean and the Gulf of Mexico, it is likely that gene flow around the Florida peninsula is restricted in
431   small coastal species due to comparatively localized movement patterns (Kohler *et al.* 1998). Both
432   the Gulf of Mexico stocks of blacknose shark and bonnethead are considered genetically separate
433   stocks (Portnoy *et al.* 2014). Bonnethead have been shown to exhibit variation in life history
434   parameters on a much smaller spatial scale along the Atlantic coast (Frazier *et al.* 2013) and within
435   the Gulf of Mexico (Lombardi-Carlson *et al.* 2003). Ultimately, while Atlantic sharpnose shark
436   within the southeast U.S. coast and within the Gulf of Mexico represent a single genetic stock
437   (SEDAR 2013), it has been suggested that migrations between the U.S. east coast and Gulf of Mexico
438   are rare for the species (Kohler *et al.* 1998). It is not surprising to note that there appears to be
439   more localized variability in small coastal shark abundance as demonstrated by the increased
440   number of common trends estimated for the Atlantic sharpnose shark and conflicting factor
441   loadings in the blacknose shark.

442   Regional increases in the Atlantic sharpnose shark, blacknose shark, and bonnethead
443   common trends also correspond with localized management implementation such as BRDs. For
444   example, following the 1998 BRD mandate in the southeast Atlantic coast (Scott-Denton *et al.*

445   2012), abundance of the Atlantic stocks of Atlantic sharpnose shark, blacknose shark, and

446   bonnethead, all significantly driven by the SEAMAP-SA Trawl, increased. Similarly, the Atlantic

447   sharpnose shark trend in the Gulf of Mexico showed an abrupt increase following the mandatory

448   implementation of BRDs in the eastern Gulf in 2004 (Scott-Denton *et al.* 2012). All small coastal

449   shark stocks showed overall increased abundance into the 2010s except the Gulf of Mexico

450   blacknose shark, which are known to be largely susceptible to bycatch within the shrimp trawl

451   fishery and likely further depleted than the Atlantic stock (SEDAR 2011). Additional survey data

452   within the Gulf of Mexico will greatly aid interpretations of coast-wide patterns of relative

453   abundance in the bonnethead.

454   *Dynamic factor analysis drivers*

455   Although several studies have linked small- and meso-scale shark distributions to climatic

456   indices (Carlson 1999; Cotton *et al.* 2005; Brodziak and Walsh 2013; Hoffmayer *et al.* 2014; Mitchell

457   *et al.* 2014; Báez 2015), studies have rarely examined whether broad-scale relative stock

458   abundance is affected by multidecadal oscillations. Although Perry *et al.* (2005) noted that slower

459   growing species (like sharks) are less likely to undergo distributional shifts due to changing

460   environmental conditions and are thus, more susceptible to changes in climate, conclusions from

461   the current study suggest that when immediate environmental conditions are unfavourable, the

462   coastal shark species examined may redistribute to more suitable conditions. For instance, although

463   blacknose sharks rarely migrate northward into Virginia waters and instead reside off the coast of

464   North and South Carolina during summer (Castro 2011 and references therein, Ulrich *et al.* 2007),

465   due to extremely warm water temperatures in the southeastern U.S. coast in the summer of 2015

466   (positive AMO and NAO indices), the VIMS LL captured 16 blacknose sharks compared to only eight

467   specimens previously recorded between 1973 and 2014. Similar accounts of distributional shifts in

468   sharks due to unfavourable environmental conditions have been documented (Wiley and

469   Simpfendorfer 2007; Nye *et al.* 2009; Sunday *et al.* 2012). Last *et al.* (2011) investigated the change

470   in species composition along the coast of Tasmania, Australia, an area subjected to extreme

471   temperature increases over the past 60 years, and found that five out of 10 elasmobranch species

472   examined exhibited distributional changes.

473   In the current study, during years when the AMO index was in its warm phase, reflective of

474   increased rainfall in Florida and heightened hurricane activity in the Atlantic Ocean, relative

475   abundance of blacktip shark was below average off the coast of Virginia and above average off

476   South Carolina. Blacktip sharks may therefore restrict their northward migration and reside in

477   more southerly areas due to unfavourable environmental conditions associated with above average

478 AMO index values. Additionally, the GULFSPAN GN, a latitudinally constant juvenile survey within
479 which 95% of blacktip shark captured were of neonatal or juvenile life stage, showed a positive
480 association with the AMO, suggesting better recruitment years and potentially higher nursery
481 habitation in the Gulf of Mexico in years when the AMO index is positive.

482 Positive NAO index values also result in increased temperatures and rainfall off the
483 southeast coast of the United States, and such environmental conditions corresponded with below
484 average sandbar shark relative abundance off Virginia and above average relative abundance off
485 Georgia. As such, environmental conditions associated with positive NAO values may lead to
486 restricted northward migration of the sandbar shark. A similar explanation likely underlies climate
487 induced distributional changes of the blacknose shark, in which relative abundance is higher off
488 South Carolina and nursery utilization and recruitment was inhibited within the Gulf of Mexico
489 during years with above average NAO values. Because the tiger shark range is so large and vast
490 migrations are common (Kohler *et al.* 1998; Lea *et al.* 2015), the data in this study are likely still
491 representative of localized relative abundance, such that tiger shark distribution patterns may shift
492 from the Gulf of Mexico to areas outside of those sampled by surveys when the NAO index is low.
493 Further empirical research will be necessary to fully understand the underlying physiological
494 linkages governing the species-specific responses to these climatic drivers.

495 Given the functionally equivalent patterns of common trends generated from models with
496 and without climatic drivers, it is reasonable to conclude that the overall abundance of coastal
497 shark stocks was not altered by environmental and anthropogenic drivers, as similarly noted by
498 Bigelow *et al.* (1999) in a pelagic shark. Rather, effects of climatic drivers within the optimal DFA
499 models were survey-specific and likely indicative of localized distributional reorganization, while
500 the estimated DFA trends reflect underlying patterns in relative abundance over broad geographic
501 scales. These regional distributional changes due to climatic forcing may be the mechanism
502 underlying local ecosystem reorganization noted by several studies (Stenseth *et al.* 2002 and
503 references therein; Collie *et al.* 2008; Nye *et al.* 2009; 2014; Karnauskas *et al.* 2015).

504 While it is expected that any substantial top-down forcing would affect shark stock
505 abundance, the estimated harvest effects differed by survey or location when included in the
506 optimal DFA model. For example, overall tiger shark landings did not significantly affect CPUE off
507 the coast of Virginia but were positively related to the SEFSC LL relative abundance in the Gulf of
508 Mexico. Landings from the Atlantic and Gulf of Mexico were necessarily pooled for analysis. Lack of
509 spatially resolved harvest information, potential changes in the distribution of tiger shark fishing
510 and bycatch over the 40-year span of the current study, a lack of information regarding differential

511 habitat use, and vast migratory patterns (Lea *et al.* 2015) creates uncertainty in understanding true
512 impacts of tiger shark landings along the southeast U.S. coast. In years when tiger shark abundance
513 along the southeast U.S. was high, they were more available to both survey gear and commercial
514 fishermen, reflective of the close correlation between the DFA common trend and tiger shark
515 landings.

516 *Dynamic factor analysis modelling*

517 Resulting broad-scale trends in relative abundance were successfully generated for the
518 species examined, as indicated by model diagnostics and the alignment between the common
519 trends, species' life history parameters, and historical management measures. Marine ecological
520 applications of DFA models have indeed increased in recent years (Chen *et al.* 2006; Azevedo *et al.*
521 2008; Katara *et al.* 2011; Tam *et al.* 2013; Colton *et al.* 2014; Stachura *et al.* 2014; Thorson *et al.*
522 2015; Buchheister *et al.* 2016) which signifies the general applicability of the method. Dynamic
523 factor analysis models provide the necessary flexibility for fisheries time series data,
524 accommodating for temporal autocorrelation short and nonstationary time series, as well as time
525 series with missing values.

526 Despite the appealing flexibility of DFA modelling, we note that the application in the
527 current study was limited. Although several coastal species are known to represent genetically
528 distinct stocks in the Atlantic and within the Gulf of Mexico (e.g., Portnoy *et al.* 2014), we chose to
529 include all survey indices in the same DFA model, regardless of location. We assumed that if the two
530 stocks showed differences in relative abundance trends over time, model selection would favour
531 estimation of two common trends, as in the Atlantic sharpnose shark. Since sharks represent
532 relatively "data limited" species, we did not have sufficient positive observations to build age- or
533 size-structure into analyses. As such, limited size ranges were likely disproportionately represented
534 in the common trend, depending on the gear configurations and sampling domains of surveys that
535 most contributed to the resulting trend. Likewise, gear-selectivity was not accounted for within the
536 DFA models. Although it can be beneficial to include multiple gear types within an analysis to
537 ensure that each species was adequately represented (e.g. bonnethead; Ulrich *et al.* 2007),
538 aggregating data from gears with different selectivities implies that resulting trends of relative
539 abundance may not explicitly represent the true patterns in length-frequency of the stock. A similar
540 argument can be made regarding potential incongruence among the estimated common trends and
541 the cumulative age composition of each stock. Representative selectivity functions for each DFA
542 common trend may be calculated by averaging the selectivity functions of each gear implemented
543 (if known), where the relative contribution of the selectivity function for each survey is weighted by

544 the corresponding factor loading. However, when size and age classes are pooled and if we assume
545 that gear selectivity and length-distribution of the catch has been largely constant over time (or
546 varies randomly), then the effect of correcting CPUE from a single survey based on the
547 corresponding gear selectivity would effectively scale the predicted estimate of relative abundance.
548 By standardizing (z-scoring) indices of relative abundance prior to DFA modelling, the effect of
549 scaling the indices to account for gear selectivity is essentially removed. Standardization also
550 removes the effect of scaling differences due to gear-specific catchability (q), where catchability is
551 the proportionality constant relating CPUE to total abundance (N; CPUE = qN; Quinn and Deriso
552 1999). Without known selectivity functions or catchability estimates for each survey, these
553 methods represent a best attempt to handle available data. Furthermore, a hierarchical model also
554 designed to reconcile conflicting indices of abundance was shown to be largely insensitive to
555 variability in gear selectivity (Conn 2010). Given additional data, DFA models may be run on
556 separate age- or size-classes or comparable gear types.

557 *Conclusions*

558 Availability of fisheries-independent data for shark species within the U.S. appears to be
559 much greater than comparable data available elsewhere in the world. Largely, global magnitudes of
560 shark stock declines in open ocean areas and other regions of the world are based on estimated
561 fisheries catch (i.e., Stevens *et al.* 2000; Clarke *et al.* 2006; Worm *et al.* 2013; Dulvey *et al.* 2014;
562 Davidson *et al.* 2016) or density-dependent data (i.e., Baum *et al.* 2003; Baum and Myers 2004;
563 Baum and Blanchard 2010), and vulnerability is assessed by life history information as opposed to
564 quantitative assessments of stock abundance (e.g., Field *et al.* 2009; Worm *et al.* 2013; Dulvy *et al.*
565 2014). The global status of these stocks is further complicated by the presence of illegal,
566 unreported, and unregulated fishing (Clarke *et al.* 2006), which is concentrated in the Indo-West
567 Pacific region where management is generally absent (Stevens *et al.* 2000; Field *et al.* 2009; Lam
568 and de Mitcheson 2011). Consequently, the currently available analyses of global shark stocks are
569 generally accompanied by operational challenges (e.g., lack of accurate landings and discard
570 information, unknown alterations in fishery-dependent fishing procedures, reliance on a single
571 index of relative abundance) and fail to provide comprehensive quantitative evidence supporting
572 claims of stock status and abundance trends. As a result, population dynamics information on
573 sharks is relatively limited (Field *et al.* 2009). A recent study by Worm *et al.* (2013) created a global
574 compilation of estimated values of fishing mortality for 21 assessed shark stocks (representing 17
575 species). Out of the 13 coastal stocks included, 11 observations of exploitation rate were obtained
576 from stocks within the U.S., emphasizing the scarcity of such information elsewhere.

577   Despite the general paucity of fisheries-independent shark survey data worldwide, a few
578   investigations of coastal shark trends in relative abundance have been made, indicating the regional
579   specificity in shark abundance trends over time. Protective beach nets in Australia and South Africa
580   have produced a relatively long time series of survey information (Dudley and Simpfendorfer 2006;
581   Reid *et al.* 2011). In southeast Australia, significant declines between 1950 and 2010 were reported
582   for four taxonomic shark groups, including Carcharhinid sharks that were pooled due to a lack of
583   species specific reporting prior to 1998. Three groups, including tiger shark, showed no significant
584   change in relative abundance, and one group showed a significant increase in relative abundance
585   (Reid *et al.* 2011). In South Africa, out of the 14 pelagic and coastal species for which indices of
586   relative abundance could be generated, only three showed significant declines in relative
587   abundance from 1978 to 2003, and one species, the tiger shark, showed a statistically significant
588   increase in relative abundance (Dudley and Simpfendorfer 2006). A compilation of opportunistic
589   data from the Mediterranean Sea showed large declines in abundance for five species comprising
590   four families, such that authors considered these large shark species to be functionally extinct
591   (Ferretti *et al.* 2008).

592   Management implementation is improving across the globe, as the International Plan of
593   Action for Sharks (IPOA-Sharks), a voluntary call for shark management from independent states,
594   was established in 1999. However, the IPOA-Sharks program currently does not include formal
595   enforcement of accountability and adoption of the program has been slow (Davis and Worm 2013).
596   Global shark landings have decreased in recent years, although further investigation revealed that
597   decreasing catch was reflective of reduced shark abundance as opposed to implementation of
598   conservative harvest policies (Davidson *et al.* 2016).

599   In conjunction with declines in the eastern U.S., global declines in shark catch and bycatch
600   have been reported into the early 2000s (e.g., Stevens *et al.* 2000; Dulvy *et al.* 2014). The method
601   presented in the current study does not enable us to estimate the magnitude of stock decline for the
602   species examined from 1975 to the early 1990s. Nevertheless, after a relatively protracted period of
603   low abundances following management implementation, common trends produced for the four
604   large coastal species presented show increases in abundance, indicative of preliminary signs of
605   recovery in U.S. Atlantic coastal shark stocks.

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874   **Tables and Figures**

875   Table 1. The optimal dynamic factor analysis (DFA) models fitted to indices of abundance derived from delta-
876   lognormal GLMs for each species. The number of common trends is denoted by *m*. Covariance matrix
877   structure refers to the *H* covariance matrix which specifies observation error. Mean Fit is a relative measure
878   of model fit calculated by summing the squared residuals of the fitted DFA common trends and dividing by
879   the sum of the squared observations (delta-lognormal indices) for each survey, and averaging the values for
880   each species. Larger values (≳0.6) indicate poor overall fit (Zuur et al. 2003b). Survey abbreviations as
881   follows: Virginia Institute of Marine Science Longline Survey (VIMS LL), South Carolina Coastal Longline
882   Survey (SC LL), Georgia Red Drum Longline Survey (GA LL), SouthEast Area Monitoring and Assessment
883   Program-South Atlantic Coastal Trawl Survey (SEAMAP-SA Trawl), SouthEast Fishery Science Centre
884   Longline Survey (SEFSC LL), Gulf of Mexico Shark Pupping and Nursery Gillnet Survey (GULFSPAN GN).

	m	*H*	Drivers	Surveys	ΔAICc	Mean Fit
Sandbar shark	1	diagonal and equal	NAO	VIMS LL SEFSC LL SC LL GA LL	0.000	0.1856
Blacktip shark	1	diagonal and equal	AMO	VIMS LL SEAMAP Trawl SEFSC LL GULFSPAN GN SC LL GA LL	2.3613	0.3736
Spinner shark	1	diagonal and equal	none	VIMS LL SEFSC LL GULFSPAN GN SC LL	1.0727	0.8118
Tiger shark	1	diagonal and equal	NAO + landings	VIMS LL SEFSC LL	2.5255	0.3206
Atlantic sharpnose shark	2	diagonal and unequal	none	VIMS LL SEAMAP Trawl SEFSC LL GULFSPAN GN	0.000	0.4905

				SC LL		
				GA LL		
Blacknose shark	2	diagonal and equal	NAO	SEAMAP Trawl SEFSC LL GULFSPAN GN SC LL GA LL	2.7372	0.5522
Bonnethead	2	diagonal and equal	none	SEAMAP Trawl GULFSPAN GN SC LL GA LL	7.1341	0.5238

Figure 1. Map of representative stations/sites sampled (for the 2012 sampling year) within each survey: Virginia Institute of Marine Science Longline Survey (VIMS LL), South Carolina Coastal Longline Survey (SC LL), Georgia Red Drum Longline Survey (GA LL), SouthEast Area Monitoring and Assessment Program-South Atlantic Coastal Trawl Survey (SEAMAP-SA Trawl), SouthEast Fishery Science Centre Longline Survey (SEFSC LL), Gulf of Mexico Shark Pupping and Nursery Gillnet Survey (GULFSPAN GN). Map generated using the rworldmap package in R (South 2011). Note that the SEFSC LL sampling has excluded the southeast coast during the years 2001, 2003, and 2007.

Figure 2. Standardized (Z-scored) drivers examined within the dynamic factor analysis (DFA) models from 1975-2014. a) Environmental drivers include North Atlantic Oscillation index (NAO), Atlantic Multidecadal Oscillation (AMO), and annually averaged sea surface temperature (SST), while b) anthropogenic drivers included species-specific landings.

Figure 3. Standardized indices of abundance for a) sandbar shark, b) blacktip shark, c) tiger shark, d) spinner shark, e) Atlantic sharpnose shark, f) blacknose shark, and g) bonnethead, representative of data conflict. Survey abbreviations are as follows: Virginia Institute of Marine Science Longline Survey (VIMS LL), SouthEast Area Monitoring and Assessment Program-South Atlantic Coastal Trawl Survey (SEAMAP-SA Trawl), SouthEast Fishery Science Centre Longline Survey (SEFSC LL), Gulf of Mexico Shark Pupping and Nursery Gillnet Survey (GULFSPAN GN), South Carolina Coastal Longline Survey (SC LL), Georgia Red Drum Longline Survey (GA LL).

Figure 4. Common trends produced from dynamic factor analysis (DFA) using delta-lognormally derived indices of relative abundance for the large coastal shark (LCS) complex. Trends (solid lines) and 95% confidence intervals (shaded regions) are displayed for a) sandbar shark, c) blacktip shark, e) tiger shark, and g) spinner shark, and factor loadings for b) sandbar shark, d) blacktip shark, f) tiger shark, and h) spinner

907 shark are shown. Factor loadings greater than 0.2 correspond to indices that had a relatively strong influence

908 on the resulting common trend, and negative factor loadings denote indices that follow an opposite trend to

909 the DFA common trend.

910 Figure 5. Common trends produced from dynamic factor analysis (DFA) using delta-lognormally derived

911 indices of relative abundance for the small coastal shark (SCS) complex. Trends (solid lines) and 95%

912 confidence intervals (shaded regions) are displayed for the a) Atlantic sharpnose shark, c) blacknose shark,

913 and e) bonnethead, and factor loadings for the b) Atlantic sharpnose shark, d) blacknose shark, and f)

914 bonnethead are shown. Factor loadings greater than 0.2 correspond to indices that had a relatively strong

915 influence on the resulting common trend, and negative factor loadings denote indices that follow an opposite

916 trend to the DFA common trend.

917

918 *Supporting information legend*

919 <u>Supplement 1: dynamic factor analysis model fitting</u>

920 <u>Supplement 2: additional tables and figures</u>

921 Table S1. Summary of surveys included in the analyses.

922 Table S2. Life history information for shark species included in analyses.

923 Table S3. Covariates included in optimal delta-lognormal generalized linear model used to calculate indices of

924 abundance for each species-survey combination.

925 Figure S1. Fitted dynamic factor analysis trends superimposed on survey-based delta-lognormally generated

926 indices of relative abundance for large coastal shark species.

927 Figure S2. Fitted dynamic factor analysis trends superimposed on survey-based delta-lognormally generated

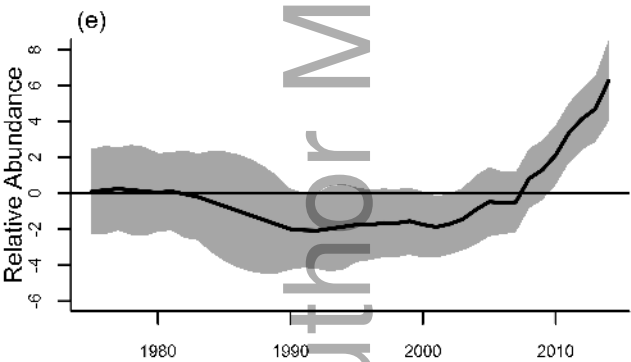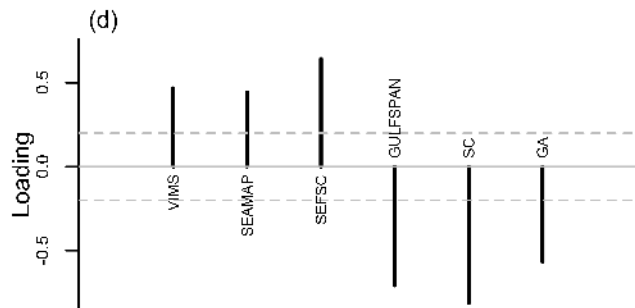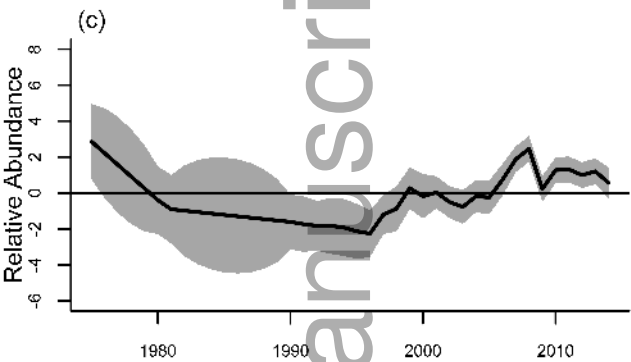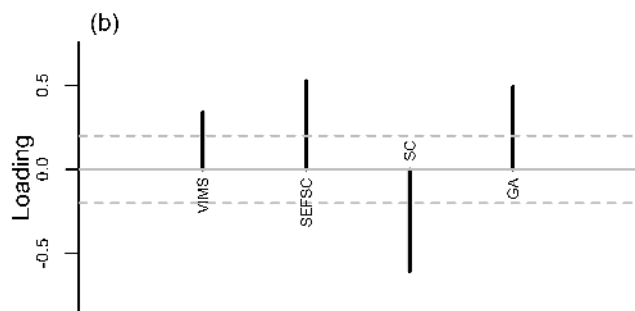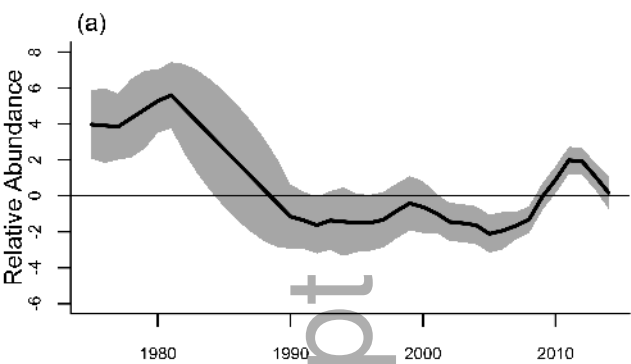928 indices of relative abundance for small coastal shark species.

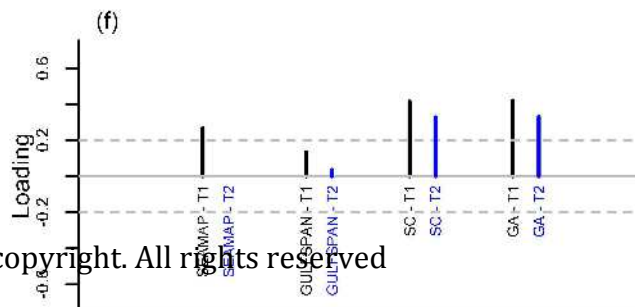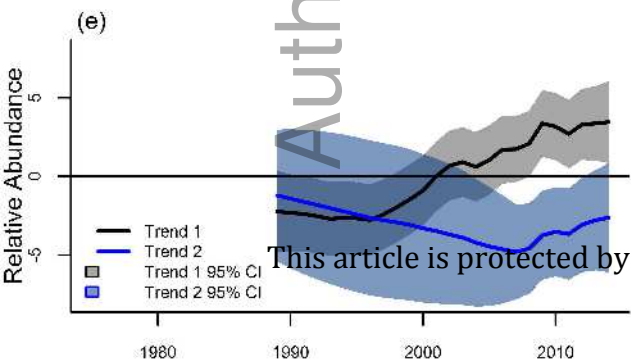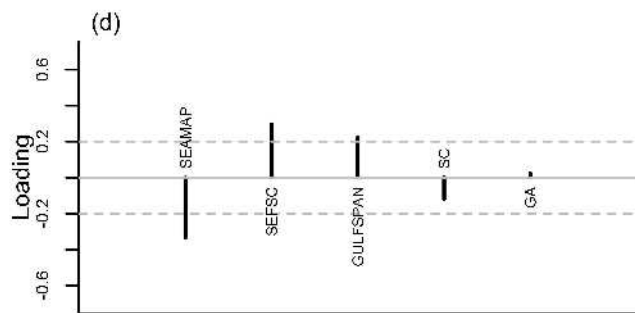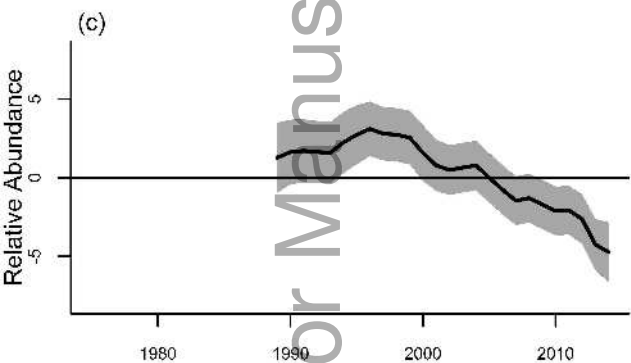929 Table S4. Dynamic factor analysis model fitting for each species.

930 Table S5. Dynamic factor analysis model results for each species.

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Legend:
- VIMS LL
- SEAMAP Trawl
- SC LL
- GA LL
- SEFSC LL
- GULFSPAN GN

(a)

(b)
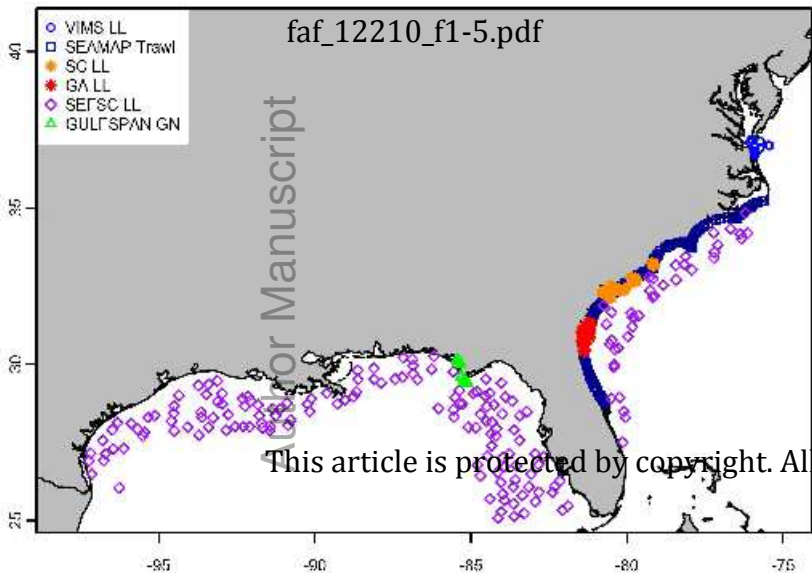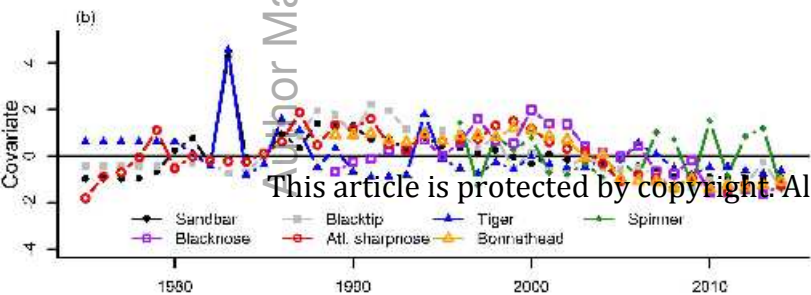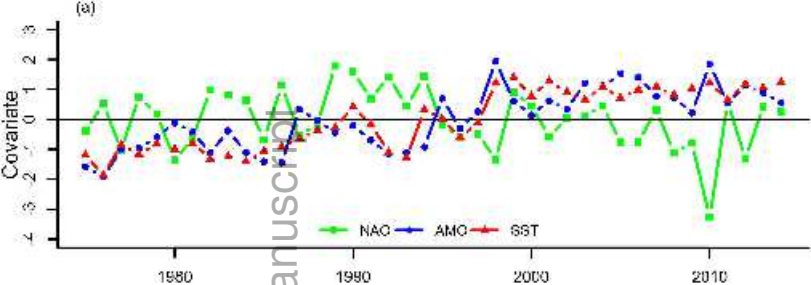
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Legend (a): NAO, AMO, SST

Legend (b): Sandbar, Blacktip, Tiger, Spinner, Blacknose, Atl. sharpnose, Bonnethead