1 **Coherence among Oregon Coast coho salmon populations highlights increasing relative**
2 **importance of marine conditions for productivity**
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4 RH: Oregon Coast coho salmon productivity
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39

40 **Abstract**
41 Anadromous fishes, such as Pacific salmon, spend portions of their life cycle in freshwater and
42 marine systems, thus rendering them susceptible to a variety of natural and anthropogenic
43 stressors. These stressors operate at different spatiotemporal scales, whereby freshwater

44   conditions are more likely to impact single populations or sub-populations, while marine
45   conditions are more likely to act on entire Evolutionarily Significant Units (ESUs). Coherence in
46   population parameters like survival and productivity can therefore serve as an indicator of
47   relative influence. The goal of this study was to elucidate scale-dependent shifts in Oregon Coast
48   coho salmon productivity. We used a multivariate state-space approach to analyze almost sixty
49   years of stock-recruitment data for the Oregon Coast ESU. Analyses were conducted separately
50   for time periods prior to and after 1990 to account for improvements in abundance estimation
51   methods and significant changes in conservation and management strategies. Prior to 1990,
52   productivity declined for most Oregon Coast populations, especially through the 1980s. From
53   1990-on, coherence increased and trends tracked closely with the North Pacific Gyre Oscillation
54   (NPGO). The latter period is associated with reductions in harvest rates and hatchery production
55   such that the relative influence of the marine environment may have grown more apparent
56   following the removal of these stressors. Furthermore, the link between productivity and NPGO
57   is consistent with trends observed for several other Pacific salmon ESUs. If Oregon Coast coho
58   salmon populations become more synchronous, managers can expect to face new challenges
59   driven by reductions in the population portfolio effect and increasingly variable marine
60   conditions due to climate change.
61
62   **Keywords:** climate indices, coho salmon, dynamic factor analysis, multivariate state-space
63   models, population dynamics, productivity, time series

1. Introduction

Over the past century, aquatic species in freshwater and marine ecosystems have been increasingly influenced by a multitude of stressors including climate change, overharvesting, and human encroachment on historical habitat (Johnson and Welch 2009, Brander 2010, Pratchett et al. 2011, Wilberg et al. 2011, Arthington et al. 2016). Anadromous species, such as Pacific salmon (*Oncorhynchus* spp.), are likely to experience these stressors more acutely because they spend large portions of their life cycle in both freshwater and marine habitats (Quinn 2005, Cunningham et al. 2018, Crozier et al. 2021). As an invaluable ecological, economic, and cultural resource, managers throughout the Pacific Coast of North America have recognized the importance of promoting healthy and stable salmon populations through sustainable harvest quotas, responsibly managed hatcheries, and habitat conservation and restoration actions. Nevertheless, many Pacific salmon populations have continued to decline despite an unprecedented level of investment in species and habitat conservation (Peterman and Dorner 2012, Ward et al. 2015, Wilson et al. 2022).

Conservation of anadromous species is inherently difficult because stressors operate across multiple spatial and temporal scales (Crozier et al. 2008, Schindler et al. 2008, Ohlberger et al. 2016, Crozier et al. 2021). For Pacific salmon, populations are sensitive to watershed-specific environmental stressors such as water temperature, salinity, stream flow, and hydrological connectivity during freshwater and early marine rearing (Mueter et al. 2002, Mueter et al. 2005, Pyper et al. 2005). When populations are more sensitive to these local-scale environmental drivers, strong spatial patterns emerge whereby survival, productivity, and other metrics of population health tend to have little spatial autocorrelation. Conversely, when ocean-scale drivers dominate, they favor high synchrony and high spatial autocorrelation in population metrics. Thus, the degree of coherence and spatial autocorrelation among populations is indicative of the scale at which stressors impact their survival and productivity (Ohlberger et al. 2016, Ruff et al. 2017, Dorner et al. 2018). This has implications for management because conservation and policy efforts tend to operate at local or regional scales (e.g., streams, watersheds), while climate-mediated shifts in ocean conditions are nearly impossible to manage (Schindler et al. 2008).

Managers and policymakers have enacted numerous conservation strategies to bolster survival and productivity. In the conterminous United States, more than 30 Pacific salmon stocks

95 (or Evolutionarily Significant Units; ESUs) are listed as threatened or endangered under the U.S.

96 Endangered Species Act (ESA; 16 U.S.C. §§ 1531–1544), ranging in geographic scope from

97 Southern California to Puget Sound, Washington. Under ESA-listing, commercial, recreational,

98 and tribal harvest is limited. To compensate for reductions in wild salmon harvest, some

99 managers have bolstered hatchery production to support sustainable fisheries, while others have

100 reduced hatchery operations in hopes of promoting a recovered wild salmon stock (these

101 strategies are not always used exclusively; Kostow 2009, Flagg 2015). Regardless, the ecological

102 and genetic risks associated with hatchery programs are widely recognized (Waples 1991,

103 Nickelson 2003, Myers et al 2004, Buhle et al. 2009).

104   The Oregon Coast coho salmon (*O. kisutch*) is one example of an ESU where hatchery

105 production was sharply curtailed concurrently with ESA-listing and reductions in maximum

106 allowable harvest rates (Fig. 1). Peak releases of over 27 million hatchery smolts occurred in

107 1981. Since the ESU was declared threatened in 1998, smolt production has been further reduced

108 from roughly 2.1 million to about 260,000 hatchery smolts, and hatchery-origin spawners have

109 declined accordingly from a maximum of 31,530 individuals in 1986 to a minimum of 662

110 individuals in 2015 (Falcy and Suring 2018). In addition, hundreds of millions of dollars (USD)

111 of investments in freshwater habitat restoration were carried out through much of the 1990s and

112 the beginning of the 21st century largely for the benefit of salmon (Nicholas et al. 2005, OWEB

113 2017). This distinct shift in management strategies for Oregon Coast coho salmon poses a unique

114 opportunity to evaluate the relative impacts of local-scale conservation actions and ocean-scale

115 processes driving productivity trends.

116   To date, robust evaluations of scale-dependent factors have been challenging because

117 changes in Oregon Coast coho salmon conservation and management occurred concurrently with

118 a recognized regime shift in the North Pacific Ocean. In 1977 and 1989, distinct change points

119 were observed for ocean indicators such as sea surface temperature and the Pacific Decadal

120 Oscillation (PDO), with implications for numerous commercial fisheries (Hare and Mantua

121 2000). PDO is a measure of Pacific climate variability that exhibits periodicity on a scale of 15–

122 25 and 50–75 years, and has historically been aligned with salmon survival (Mantua and Hare

123 2002); however, following the regime shift in 1989, the North Pacific Gyre Oscillation (NPGO)

124 began to display a stronger relationship to salmon survival than PDO (Kilduff et al. 2015, Litzow

125 et al. 2018). This shift was also accompanied by a general breakdown in the correlation between

126   salmon abundance (i.e., run strength) and traditional ocean indicators. The drivers and

127   implications of these regime shifts and their influence on salmon population health are a topic of

128   ongoing research and discussion.

129   In order to disentangle scale-dependent shifts in Oregon Coast coho salmon population

130   dynamics, we evaluated spatial and temporal trends in population productivity using historical

131   survey data. We addressed the following questions: 1) How have productivity trends changed

132   following the implementation of conservation efforts and a concurrent oceanic regime shift in the

133   mid-1990s? 2) How similar are productivity trends among populations, and has synchrony in

134   productivity changed through time? 3) Is productivity influenced by freshwater and/or marine

135   rearing conditions? To answer these questions, we used a multivariate state-space approach to

136   quantify coherence in productivity through space and time and to relate productivity to several

137   environmental covariates. Multivariate state-space models are particularly useful for analyzing

138   ecological time series data due to their ability to partition process and observation error and

139   handle missing data (Zuur et al. 2003, Dennis et al. 2006, Ward et al. 2010). Results from this

140   approach will provide important information on how ESA-listed Oregon Coast coho salmon

141   population dynamics have shifted through time, and how conservation efforts and changing

142   marine conditions may be influencing population trends.

143

144   **2. Methods**

145   *2.1 Population structure*

146   The Oregon Coast coho salmon ESU is comprised of 56 historical populations that are

147   reproductively and behaviorally distinct from other coho salmon populations in the Pacific

148   Northwest, USA (Lawson et al. 2007). The ESU's geographical range spans most of the Oregon

149   Coast and is bounded by the Necanicum River to the north and the Sixes River to the south. For

150   this analysis, we focused on 21 independent populations (i.e., those populations with a high

151   likelihood of persisting in isolation from neighboring populations; Chilcote et al. 2005) and

152   omitted dependent populations (i.e., populations that were most likely to rely on periodic

153   immigration from other populations to maintain their abundance). Independent populations were

154   grouped into five biogeographic strata with distinct genetic and geographic structure: North

155   Coast, Mid-Coast, Lakes, Umpqua River, and Mid-South Coast (Lawson et al. 2007; Fig. 2,

156   Table 1).

157

2.2 Stock-recruitment and productivity data

Oregon Department of Fish and Wildlife (ODFW) has consistently monitored spawning populations of Oregon Coast coho salmon since the mid-1950s. We used 59 years (1958–2016) of stock-recruitment time series data to evaluate productivity trends for the entire ESU and for each biogeographic stratum (Chilcote et al. 2005). We calculated productivity as the natural logarithm of the number of adult recruits per spawner, $log_e(R_{t+3}/S_t)$, where S_t is the estimated total number of natural and hatchery origin fish on the spawning grounds in year t, and R_{t+3} is the number of pre-harvest, natural origin adult recruits returning three years later. Hatchery origin fish are included in S_t because adult strays may produce natural progeny, but they are excluded from R_{t+3} because they are not the progeny of naturally spawning fish themselves. Nearly all coho salmon mature and return to spawn as three-year-olds (Pearcy 1992). Precocious returns ("jacks") were omitted from the analysis. To facilitate comparisons among populations, productivity data were standardized (*z*-transformed) by subtracting the mean from each value and dividing by the standard deviation.

We analyzed pre-1990 and post-1990 data separately to account for potential discrepancies in monitoring methodology, management practices, and the reliability of population estimates. Sampling methods have shifted throughout the previous few decades and have generally become more reliable through time. Population estimates prior to 1990 were derived from index site sampling, whereby abundance estimates were based on calibrations of peak counts from non-random index surveys that tended to favor the reliable presence of fish. For analytical purposes, these peak counts were calibrated against abundance estimates derived from randomly selected spawning surveys during a period when the two methods were employed concurrently (1990–2003). ODFW switched from index site sampling to stratified random sampling in 1990 and then to generalized random tessellation sampling (a spatially balanced sampling design) in 1998 (Jacobs and Nickelson 1998, Rupp et al. 2012a, Falcy and Suring 2018). Additionally, as mentioned above, major management shifts occurred in the 1990s. ESA-listing of Oregon Coast coho in 1998 resulted in an almost 90% reduction in ocean and freshwater harvest rates, while hatchery production also declined substantially through the 1990s after peaking in the late-1980s (Fig. 1; Melcher 2005, Falcy and Suring 2018).

187   Model-based estimation of time-varying observation errors can be difficult; however,

188   conducting separate analyses allowed us to account for these "change points" in methodology

189   and management practices that were likely to affect observation error structure and productivity

190   through time. It also allowed us to directly address our first study question regarding shifts in

191   productivity trends following the implementation of conservation efforts and a concurrent

192   oceanic regime shift in the mid-1990s. Pre-1990 analyses were not conducted for the Salmon,

193   Floras, or Sixes populations due to missing data.

194

195   *2.3 Environmental covariates*

196   To examine the relative importance of freshwater and marine rearing conditions for Oregon

197   Coast coho salmon productivity, we fit models with environmental covariates that were expected

198   to affect salmon in their first or second year of life (Table 2). Covariates that were expected to

199   affect coho salmon during freshwater rearing (Year 1) included average summer air temperature

200   over land (a reliable proxy for aquatic thermal conditions and streamflow in rain-fed systems)

201   and average winter precipitation. Covariates that were expected to affect coho salmon during

202   early marine residence (Year 2) included the average annual Pacific Decadal Oscillation (PDO)

203   and North Pacific Gyre Oscillation (NPGO), both of which have been linked to the survival of

204   Pacific salmon populations and are correlated with other marine drivers such as sea-surface

205   temperature, salinity, nutrient availability, and productivity (Di Lorenzo et al. 2008, Kilduff et al.

206   2015). All environmental variables were *z*-transformed prior to analysis to allow comparison of

207   the magnitude of estimated effects.

208

209   *2.4 Correlations among populations*

210   To evaluate spatial and temporal coherence in productivity, we calculated pairwise Pearson's

211   correlation coefficients (*r*) for each independent population of coho salmon. Correlation

212   coefficients were calculated separately for the pre- and post-1990 time periods. We then

213   estimated mean and standard deviation correlation within and among strata.

214   To determine whether the degree of covariation decreased with increasing distance (i.e.,

215   to quantify spatial coherence), we fit an exponential decay function:

216    $$\rho_\delta = \rho_0 e^{-\delta/v}$$

217 where ρ is Pearson's correlation coefficient for each pairwise comparison of productivity

218 between independent populations and δ is the distance between populations at the point of

219 marine entry (Pyper et al. 2002, Kilduff et al. 2014, Zimmerman et al. 2015). The parameter v is

220 the e-folding scale (the distance at which correlation is expected to decrease by e^{-1} or 37%) and

221 the parameter ρ_0 is the intercept (expected correlation at $\delta = 0$). The exponential decay function

222 was fit separately for pre- and post-1990 data using non-linear least squares in R (R

223 Development Team 2020). Distances among points of marine entry were estimated using

224 ArgGIS 10.8.1 software (ESRI, West Redlands, California, USA) as the Euclidean distance

225 between two entry points. For both time periods, we compared the fit of the exponential decay

226 model to a null model ($\rho_\delta = m$, where m represents the mean correlation among all pairwise

227 comparisons) using the Akaike Information Criterion adjusted for small sample sizes (AICc). A

228 ΔAICc value > 2 indicated modest support for the exponential decay model over the null model

229 (Burnham and Anderson 2002).

230

231 *2.5 Dynamic factor analysis*

232 To evaluate trends in productivity through time, we used dynamic factor analysis. Dynamic

233 factor analysis (DFA) is a dimension reduction technique with state-space time series models that

234 aims to explain temporal variation in multiple time series using a linear combination of shared

235 unobservable trends (Zuur et al. 2003). The model uses a multivariate, autoregressive state-space

236 approach with the following structure:

237 $$\boldsymbol{y}_t = \mathbf{Z}\boldsymbol{x}_t + \boldsymbol{a} + \mathbf{D}\boldsymbol{d}_t + \boldsymbol{v}_t$$

238 $$where \; \boldsymbol{v}_t \sim MVN(0, \mathbf{R})$$

239 It estimates the loadings (matrix $\mathbf{Z}$) on each of the hidden trends and assumes observation error

240 (v) is multivariate normally distributed (MVN) with a mean of zero and a variance-covariance

241 matrix $\mathbf{R}$. When covariates ($\boldsymbol{d}_t$) are included, the model can estimate the regression coefficients

242 for each of the covariate effects (matrix $\mathbf{D}$). Our productivity data were z-scored, so the offset

243 value ($\boldsymbol{a}$) was set to zero.

244   The true but unobserved trends ($\boldsymbol{x}_t$) are modeled as a random walk with process noise

245 ($\boldsymbol{w}_t$):

246 $$\boldsymbol{x}_t = \boldsymbol{x}_{t-1} + \boldsymbol{w}_t$$

247 $$where \; \boldsymbol{w}_t \sim MVN(0, \mathbf{I})$$

248   In the process equation, noise is also assumed to be normally distributed with a mean of zero;

249   however, for identifiability reasons the variance-covariance matrix is fixed as an identity matrix

250   **I**.

251   We conducted the DFA procedure separately for the pre- and post-1990 time periods.

252   First, we ran the analysis for the entire Oregon Coast using all 21 populations (coast-wide).

253   Then, to parse out regionally specific trends, we ran analyses separately for each stratum

254   (regional). For the coast-wide analysis, we tested models with up to three hidden trends and for

255   regional analyses we tested models with one or two hidden trends depending on the number of

256   populations in each stratum (H = 1 for N ≤ 3). We evaluated models with various observation

257   error structures: shared variance and no covariance ("diagonal and equal"), different variances

258   and no covariance ("diagonal and unequal"), or shared variance and covariance ("equal variance

259   and covariance"). We used the MARSS package in R (Holmes et al. 2012) to estimate parameter

260   values and states for all model iterations. The best-fit model was selected using AICc, where a

261   ΔAICc value > 2 indicated modest support for one model over others (Burnham and Anderson

262   2002).

263   We evaluated the relationship between environmental covariates (PDO, NPGO,

264   temperature, precipitation) and predicted productivity trends from the coast-wide and regional

265   analyses. Covariates can be directly integrated in the DFA via the d_t term in the model; however,

266   these covariate effects (**D**) are included in the observation rather than the process model. Our

267   interest is in the latter, so we also calculated correlation coefficients for the trends derived from

268   the best-fit DFA models and each environmental covariate, and used a simple, linear model to

269   evaluate whether trends were significantly correlated ($P < 0.05$) with freshwater and marine

270   conditions.

271

272   **3. Results**

273   ***3.1 Correlation among populations***

274   The degree of correlation in coho salmon productivity as measured by Pearson's correlation

275   coefficient (r) trended positive and non-zero for most pairs and was greater within than among

276   strata (Fig. 3, Table 3). Overall, the degree of correlation nearly doubled from the pre-1990 to

277   post-1990 period and increases occurred both within and among strata. Prior to 1990, within-

278   stratum correlation was strongest ($r > 0.5$) for the North Coast and Umpqua strata and was

279 weakest for the Mid-South Coast stratum. This trend was also true for productivity data collected

280 in 1990 and afterward. Lower cohesion for the Mid-South Coast stratum was likely driven by the

281 Sixes River population, whose productivity trends did not appear to coincide with those of other

282 Oregon Coast coho populations. In terms of among-stratum comparisons, the Lakes and Mid-

283 South Coast strata appeared to have productivity trends that were most different from other strata

284 and each-other, and this trend was more consistent during the post-1990 time period.

285   Within-stratum correlation was greater than among-stratum correlation in year-to-year

286 productivity prior to 1990, yet the degree of correlation among population productivity trends did

287 not decrease with increasing distance (Fig. 4). The AICc value for the null model was lower than

288 the AICc value for the exponential decay model (ΔAICc = 2.02) and the parameters for the

289 exponential decay model converged in such a way that the e-folding scale (v = 1,501 km) was

290 much larger than the extent of the Oregon Coast. From 1990-on, spatial autocorrelation was

291 detectable but was still weak (v = 1,323 km). There was marginal evidence that the fit of the

292 exponential decay function was better than the fit of the null model (ΔAICc = 1.82).

293

294 **_3.2 Dynamic factor analysis_**

295 _3.2.1 Coast-wide_

296 The coast-wide DFA using the pre- and post-1990 data sets identified several different Oregon

297 Coast coho salmon productivity trends and indicated greater coherence in population

298 productivity from 1990-on. Prior to 1990, the best-fit model estimated three trends with

299 independent and unique observation variances for each population (Table S1). Trends 1 and 2

300 were characterized by stochastic, year-to-year fluctuations in productivity between 1958 and

301 1990, with a slight dip for Trend 2 in the mid-1980s (Fig. 5). Populations in the Mid-Coast

302 stratum had the greatest loadings on Trend 2, while populations in the Umpqua River had strong

303 positive loadings on Trend 1. Trend 3 was characterized by a slight increase in productivity

304 through the mid-1980s, followed by a very sharp increase; however, loadings on this trend were

305 widespread and negative, indicating that most Oregon Coast coho salmon populations actually

306 experienced a productivity crash in the mid-to-late 1980s. The unique error structure implied that

307 there may have been among-population variation in the accuracy of abundance estimates, which

308 is consistent with what we know about calibration and estimation methods through the 1990s.

309 Observation error (R) ranged from a low of 0.16 for the North Umpqua population to a high of

310   0.85 for the Tahkenitch Lake population. R was generally low ($\leq$ 0.2) for the Middle, North, and
311   South Umpqua populations and high ($\geq$ 0.6) for the Lakes and Mid-South Coast strata, but was
312   variable among North- and Mid-Coast populations (Table S2).

313   From 1990-on, the best-fit model supported a single observation error (R = 0.82) and
314   shared covariances (R = 0.39) and identified a single productivity trend. Despite the change in
315   survey methodology and expected increase in precision for post-1990 surveys, the observation
316   error variance for this era was higher than for all but two populations pre-1990 (Table S2). The
317   estimated trend appeared to be cyclical and increasing with peaks in the late 1990s, mid-2000s,
318   and mid-2010s. Productivity correlated significantly with NPGO (r = 0.59, R^2 = 0.33, P = 0.002;
319   Fig. S1), indicating that marine processes have had a notable impact on Oregon Coast coho
320   productivity since the 1990s (Trends 1–3 from the pre-1990 DFA did not correlate significantly
321   with NPGO or PDO). Loadings were greatest for populations in the North- and Mid-Coast strata
322   and negative for the Lakes stratum and Sixes River population (Fig. 5). Drivers other than
323   marine conditions may have limited the productivity of populations with weak or negative
324   loadings.

325

326   *3.2.2 Regional*
327   Regional DFAs identified trends that were specific to individual strata. Prior to 1990, among-
328   stratum trends were highly variable (Fig. 6, Table S3). For instance, the best-fit models for the
329   North Coast and Lakes strata were characterized by an observation error structure with a single
330   variance and covariance (North Coast R_{var} = 0.69, R_{cov} = 0.20; Lakes R_{var} = 0.71, R_{cov} = 0.33),
331   and showed widespread declines in productivity through the 1980s. Loadings were generally
332   consistent among populations. For the Mid-Coast stratum, the best-fit model included two hidden
333   trends with independent and unique observation error variances (R = 0.02–0.78). Trend 1
334   demonstrated a gradual increase in productivity, with the greatest loadings from the Siletz and
335   Alsea populations. Trend 2 showed a gradual decrease in productivity and a very sharp decline
336   through the mid-1980s, with the greatest loadings from the Yaquina and Siuslaw populations.
337   For the Umpqua stratum, the best-fit model had two hidden trends with independent and unique
338   observation error variances (R = 0.01–0.88). Trend 1 exhibited a steady-but-slight decline
339   through the late 1970s with a sharp decline thereafter. Trend 2 showed productivity was
340   generally steady or increasing, and was the predominant trend for the Middle, North, and South

341 Umpqua populations. The Lower Umpqua population had weak loadings on both trends,

342 indicating that productivity may have followed a separate trajectory for this population during

343 the pre-1990 time period. For the Mid-South Coast stratum, data were only available for the

344 Coos and Coquille populations. The best-fit model had a single observation error variance (R =

345 0.87) and demonstrated a declining trend that was similar to those observed for the North Coast

346 and Lakes strata.

347   From 1990-onward, productivity trends became much more cohesive (Fig. 7, Table S3).

348 Most predicted trends were similar to what was observed for the coast-wide DFA, with peaks in

349 the late 1990s, mid-2000s, and mid-2010s. This pattern was exhibited by the North Coast (single

350 observation error variance, R = 0.28), Mid-Coast (Trends 1 and 2; unique observation error

351 variances, R = 0.08–0.67), and Umpqua populations (Trend 1; unique observation error

352 variances, R = 0.03–0.40). The best-fit model for the Mid-South Coast stratum was slightly

353 distinct in that it showed sharp peaks in productivity in the late-1990s and mid-2000s, with a

354 single observation error variance and covariance ($R_{var} = 0.77$, $R_{cov} = 0.33$). The DFA procedure

355 for the Mid-Coast stratum identified two best-fit models; one with two trends and unique

356 observation error variances and one with two trends and a single variance and covariance. From

357 here on, we report on the output for the model with unique observation error variances, which

358 had a lower root-mean-square error. Both trends for the Mid-Coast stratum were highly similar,

359 with divergence in the early 1990s. Loadings on Trend 1 were strongest for the Salmon and

360 Yaquina populations, while loadings for Trend 2 were strongest for the Siletz and Alsea

361 populations. The best-fit model for the Umpqua stratum had two trends; however, loadings were

362 very weak for Trend 2, which demonstrated a sharp increase in productivity after the year 2000.

363 The Lakes stratum was the only one with a distinct, declining trajectory, and had a single

364 observation error variance and covariance ($R_{var} = 0.87$, $R_{cov} = 0.53$).

365   Including environmental covariates in the DFA as observation error covariates did not

366 improve model fit for any of the coast-wide or regional analyses (Table S4); however, when

367 predicted trends were directly correlated with covariates, some strong relationships emerged

368 (Fig. S2–S6, Table S5). Prior to 1990, productivity for the Lakes, Umpqua (Trend 1), and Mid-

369 South Coast strata was negatively correlated with PDO, while productivity for the Mid-Coast

370 stratum was marginally correlated with summer temperature, although this relationship appeared

371 to be biologically insignificant. From 1990-onward, NPGO emerged as an important

372 environmental driver and exhibited a significantly high degree of overlap with productivity

373 trends for the North Coast ($r = 0.53$), Mid-Coast (Trend 2; $r = 0.68$), and Mid-South Coast strata

374 ($r = 0.57$; Fig. 8). PDO was also negatively correlated with productivity for the Mid-Coast

375 (Trend 2; $r = -0.46$), Umpqua ($r = -0.44$), and Mid-South Coast ($r = -0.45$) strata. Mid-Coast

376 Trend 2 was positively correlated with winter precipitation ($r = 0.41$). For Lakes populations,

377 productivity was negatively correlated with summer air temperature ($r = -0.95$), but not with any

378 of the marine drivers.

379

380 **4. Discussion**

381 We used a quantitative approach to evaluate scale-dependent shifts in productivity for 21

382 independent populations of Oregon Coast coho salmon. Our analyses supported a clear change

383 point in the 1990s whereby coast-wide declines in productivity transitioned to a more cyclical

384 pattern and regional trends became more coherent both within and among biogeographical strata.

385 There are several possible explanations for this change point and they are not necessarily

386 mutually exclusive: 1) less reliable survey methods and uncertainty in population-specific

387 harvest rates and the proportion of hatchery spawners introduced more variability and obscured

388 potential relationships with environmental drivers, and 2) a mechanistic change point in

389 productivity occurred sometime in the 1990s following a coast-wide population crash for Oregon

390 Coast coho salmon and concurrent with conservation efforts and an oceanic regime shift (Hare

391 and Mantua 2000, Falcy and Suring 2018). Our findings and the existing literature lend support

392 for the second explanation. Between 1990 and 2010, coho salmon productivity appears to have

393 tracked closely with marine conditions, especially NPGO, which is an indicator of ocean current

394 and circulation patterns and is closely linked to phytoplankton concentrations (Di Lorenzo et al.

395 2008, Kilduff et al. 2015). Increased dependence on marine conditions in the first ocean year of

396 life (as opposed to freshwater conditions, which can be highly variable among watersheds) and

397 among-population coherence demonstrate a shift from local- to broad-scale drivers of

398 productivity (Ohlberger et al. 2016, Ruff et al. 2017, Dorner et al. 2018). Furthermore,

399 reductions in hatchery production and limited harvest concurrent with ESA-listing appear to have

400 slowed declines in productivity for the Oregon Coast coho salmon ESU, even if the number of

401 recruits per spawner has not improved (Falcy and Suring 2018). We provide a more in-depth

402 discussion of these trends below.

403

4.1 Temporal productivity trends

Prior to 1990, coho salmon productivity was best described by three trends according to the DFA, and loadings on these trends varied by population. For most populations, loadings were moderately-to-strongly positive for Trend 2, which indicated that productivity fluctuated until about 1980, when it began to gradually decline. Trend 3, for which most loadings were weak and negative, pointed to a gradual decrease in productivity from about 1958 to 1984 and a steep decrease in productivity through the rest of the 1980s. When considered in tandem, these trends suggest that the 1980s were a period of starkly declining productivity for the Oregon Coast coho salmon ESU, especially for populations from the North Coast, Mid-Coast (with the exception of the Siletz and Alsea), Lakes, and Mid-South Coast strata (Fig. S7). Regional trends corroborated steep declines in productivity through the 1980s for the North Coast, Lakes, Mid-South Coast, and some of the Mid-Coast (Trend 2) strata, along with the Lower Umpqua population (Trend 1). Ocean survival through the 1980s and/or 1990s was poor for many Pacific Northwest salmon populations, including coho and Chinook salmon (*O. tshawytscha*; Loggerwell et al. 2003, Rupp et al. 2012b, Sharma et al. 2013, Falcy and Suring 2018), and steelhead trout (*O. mykiss*, which have continued to exhibit low survival rates; Kendall et al. 2017).

From 1990-on, coast-wide productivity followed a single, cyclical trend for most populations, with distinct peaks occurring in the late-1990s, mid-2000s, and mid-2010s. Regional trends for the North, Mid-, Umpqua, and Mid-South strata again corroborated coast-wide trends; however, productivity in the Lakes stratum appeared to continue to decline. Lakes coho salmon are subject to different stressors and use different life history strategies due to the region's unique geography. Adult coho salmon spawn in the various tributaries that drain into the large, shallow lakes while juveniles rear in the tributary streams or in the highly-productive lakes and surrounding marshes. Historically, optimal rearing and spawning conditions have led to higher than average juvenile salmon growth rates, relative abundance, and smolt-to-adult survival (Zhou 2000, Nickelson 2001). As such, Lakes coho salmon were previously considered to be a benchmark for the Oregon Coast ESU. This stratum continued to have high persistence and sustainability scores in the most recent ESU status review (NMFS 2022), but recent declines in productivity have highlighted uncertainty in these populations' long-term resilience. The southernmost Sixes River population also diverged from post-1990 trends in productivity in that

434 they were generally more stochastic; however, the reasons for this are less clear. Cape Blanco is

435 used as a geological dividing point between the Oregon Coast ESU and the Southern

436 Oregon/Northern California Coast (SONCC) ESU, but more analysis is needed to determine

437 whether the Sixes River population's productivity might track more closely with that of the Elk

438 River and other SONCC coho salmon populations to the south. If that were the case, it would

439 suggest this population's evolutionary history, life history characteristics, and/or behavior place

440 it more in-line with SONCC populations or as its own population unit. Studies have indicated

441 that the Sixes population is genetically distinct from other Oregon and Washington coho salmon

442 populations (Ford et al. 2004).

443

444 *4.2 Coherence among populations*

445 Pairwise comparisons of productivity using Pearson's correlation coefficient revealed strong

446 spatiotemporal trends for Oregon Coast coho salmon (particularly within strata), although there

447 was limited evidence for a decrease in covariation with increasing distance. Based on previous

448 studies using similar methods, we expected baseline rates of correlation to be high due to the

449 narrow spatial scope of our analysis, with some dampening in the decay signal (i.e., *e*-folding

450 scale). For example, the 350 km maximum distance among Oregon Coast watersheds was

451 roughly 1/6 of the maximum distance evaluated in Ruff et al. (2017), who analyzed population

452 coherence in marine survival for Chinook salmon along most of the coast of Oregon,

453 Washington, and British Columbia. Nevertheless, they did observe a measurable decay with

454 distance both along the Pacific Coast and within the Salish Sea (*e*-folding scale of 517 and 292

455 km, respectively compared to our estimates of 1,323–1,501 km). Zimmerman et al. (2015) also

456 observed relatively low *e*-folding scale values in their analysis of coho salmon smolt survival

457 (129–506 km depending on time period). Even considering differences in life history strategies

458 among species and the external factors impacting productivity vs. marine survival (Quinn 2005),

459 we would have expected a lower *e*-folding scale, especially considering that within-stratum

460 correlation was considerably greater than among-stratum correlation.

461 Pairwise correlation in productivity was consistently higher within-strata than among-

462 strata, and this was true for both the pre- and post-1990 time periods. The Umpqua River

463 populations had the greatest within-stratum correlation overall, with several likely

464 methodological and ecological explanations. Pre-1990 Middle, North, and South Umpqua

465 abundance estimates were all calibrated using counts at Winchester Dam, which explains why

466 these populations had the greatest loadings on predicted trends while Lower Umpqua loadings

467 were fairly weak. Ecologically, the four Umpqua populations out-migrate through the same river

468 mouth and are more likely to experience analogous environmental conditions while doing so.

469 This lends support to the theory that early marine conditions are critical drivers of salmon

470 survival (Mortensen et al. 2000, Beamish and Mahnken 2001, Beamish et al. 2004). Within the

471 Umpqua watershed, topography, climate, and anthropogenic influence are highly variable

472 because the river flows through two mountain ranges (the Cascades and the Coast Range) and

473 several urban areas. Based on this, one might expect to see more variability among the Umpqua

474 populations, yet within-stratum correlation in productivity was high during both the pre- and

475 post-1990 time periods. Conversely, the Mid-Coast, Mid-South Coast, and Lakes strata had the

476 lowest degree of within-stratum correlation despite experiencing very similar freshwater

477 conditions among their respective watersheds. Although the Mid-Coast and Lakes populations

478 became more coherent with each-other and with other Oregon Coast populations from 1990-on,

479 within- and among-stratum cohesion for the Mid-South Coast remained fairly low. As mentioned

480 above, from 1990-on this was driven by the Sixes River population, which had productivity

481 trends that differed from those of other populations throughout the Oregon Coast.

482   The degree of within- and among-stratum correlation among independent populations of

483 coho salmon increased between the pre- to post-1990 period for all comparisons, in some cases

484 more than doubling. Removal of stressors such as harvest and hatchery production likely

485 decreased spatial variability in the freshwater component of productivity (Falcy and Suring

486 2018). Indeed, the degree of hatchery production, which has been shown to negatively impact

487 natural origin coho salmon populations (Nickelson 2003, Buhle et al. 2009), was highly variable

488 among populations, ranging from 0–99% of spawning adults prior to 1990 (the coast-wide

489 average was 10–27% depending on year). After roughly the year 2000, hatchery production

490 declined precipitously to a coast-wide average of 1–16% of spawning adults, and the percentage

491 of hatchery spawners was consistently lower than 5% for most populations. Harvest, which was a

492 major source of pre-spawn mortality prior to ESA-listing, was estimated as a single value for the

493 Oregon Coast. The percentage of adults lost to commercial and recreational harvest ranged from

494 28–87% prior to 1990 (Lawson 1992). After ESA-listing in 1998, harvest rates were only 1–

495 20%. Substantial investments in freshwater habitat restoration, conservation, and enhancement

496   were also carried out during this time period; however, direct linkages between restoration and
497   salmon populations are challenging to detect. The extent and quality of restored habitat may not
498   yet have reached a threshold where its effects on population parameters are detectable (Roni et
499   al. 2010), and a considerable amount of variability in habitat conditions still exists among
500   watersheds. Furthermore, the process and time scale over which complete restoration occurs is
501   such that improvements in habitat quality may not transpire for decades, or even centuries, after
502   restoration actions are enacted.
503   It is possible that improved survey methods may have also contributed to increased
504   synchrony during the post-1990 time period. Surveys transitioned from the use of index sites to a
505   less biased randomized sampling design in the 1990s (Jacobs and Nickelson 1998, Rupp et al.
506   2012a, Falcy and Suring 2018). Estimation of the proportion of hatchery spawners on the
507   spawning grounds also improved through time with the widespread utilization of external
508   markings. As mentioned above, a single annual harvest rate was used for all populations, which
509   would have masked potential among-population differences in adult mortality, thus creating
510   more uncertainty in estimated productivity values prior to ESA-listing during high-harvest years.
511   When considered in tandem, these methodological factors could have certainly affected
512   productivity estimates. One benefit of using a multivariate state-space approach such as DFA is
513   that it can account for differences in observation error due to different surveying methods (Zuur
514   et al. 2003, Dennis et al. 2006, Holmes et al. 2012), whereas correlation coefficients do not
515   account for such error. In our analysis, differences in observation error pre- and post-1990 were
516   highly variable among populations and between the coast-wide and regional DFAs. The coast-
517   wide analysis did not detect a decline in observation error for all but two populations, but when
518   the analysis was split by biogeographic strata, observation error did decline for many
519   populations. Increased cohesion among population productivity was still clearly reflected in the
520   coast-wide DFA, where the number of hidden trends was reduced from 3 to 1 between the pre-
521   and post-1990 periods.
522
523   *4.3 Influence of freshwater and marine rearing conditions*
524   We tested the effects of environmental variables related to freshwater (summer temperature,
525   winter precipitation) and marine conditions (average annual PDO and NPGO) by including them
526   as covariates in the DFA models and by assessing whether they were correlated with best-fit

527 productivity trends. There was little support for covariates when they were included in the DFA,

528 but when best-fit trends were directly compared to the standardized covariates, some significant

529 correlations emerged.

530   Prior to 1990, PDO demonstrated a negative relationship with trends for the Lakes,

531 Umpqua, and Mid-South Coast strata; however, this relationship was more noticeable prior to

532 sharp regional declines in productivity through the 1980s. Aforementioned methodological

533 considerations and declines in productivity may have masked the influence of marine drivers.

534 From 1990-on, the relationship between productivity and environmental conditions became

535 much clearer for some strata. Between 1990 and 2010, coast-wide, productivity appeared to be

536 closely related to the NPGO index. This was also reflected in the regional analyses such that

537 trends for the North-, Mid-, and Mid-South Coast populations tracked closely with each other

538 and with NPGO. The NPGO index has been implicated as a driver of marine survival and

539 productivity for several salmon species (Kilduff et al. 2014, 2015, Ohlberger et al. 2016, Ruff et

540 al. 2017, Dorner et al. 2018). This is unsurprising as it is closely linked to coastal upwelling,

541 nutrient cycling, and phytoplankton and krill concentrations (Di Lorenzo et al. 2008, Sydeman et

542 al. 2013, Kilduff et al. 2014, 2015). From about 2010-on, the correlation between productivity

543 and NPGO weakened. Variance in NPGO and other ocean indicators (including PDO, which has

544 been negatively correlated with NPGO in recent years) has increased in recent decades, signaling

545 that the stability of the marine environment may be declining (Di Lorenzo et al. 2010, Sydeman

546 et al. 2013, Kilduff et al. 2014). Given the apparent relationship between salmon survival,

547 productivity, and Pacific climate, more frequent and unpredictable periods of unfavorable ocean

548 conditions may lead to destabilization of highly synchronous populations such as the Oregon

549 Coast coho salmon (Kilduff et al. 2015, Mantua 2015).

550   Site specific changes in environmental conditions may have contributed to the Lakes

551 populations' continual decline in productivity throughout the study period. For instance, in the

552 1960s, dams were built on Siltcoos and Tahkenitch lakes to control the flow of water for nearby

553 paper mills, and these dams can act as a partial barrier to upstream migration under some

554 conditions. Other factors include reduced natural seasonal variation in lake levels, eutrophication

555 due to increased nutrient inputs, harmful algal blooms, and the presence of nonnative species

556 such as bluegill (*Leponis macrochirus*) and largemouth bass (*Micropterus salmoides*), which

557 may consume juvenile salmon (Reimers 1989, Gray 2005, ODFW 2007). Productivity for these

558   populations was negatively correlated with PDO prior to 1990 and with temperature from 1990-

559   on. It is not out of the question that fish rearing in a shallow lake and its adjacent marshes during

560   their first year of life would be more sensitive to temperature than those rearing in a lotic

561   environment with access to thermal refugia. Temperature plays a major role in dictating growth

562   and metabolism for ectothermic organisms such as fish, and an extended period of exposure to

563   elevated temperatures can be lethal (Brett 1952, Richter and Kolmes 2005, Beauchamp 2009). In

564   general, the lakes are not suitable for juvenile coho salmon rearing in the summer due to water

565   quality and predation risk. Rather, they benefit coho salmon by providing high quality

566   overwintering habitat (NMFS 2016). The relationship between temperature and productivity in

567   this stratum is consistent with limited summer rearing habitat upstream from the lakes, and a

568   temperature-mediated risk of predation in the lakes themselves.

569

570   *4.4 Management implications*

571   Our analysis of spatiotemporal trends in Oregon Coast coho salmon productivity yielded

572   information that will be useful for researchers and managers. The time series analysis was

573   indicative of a change in both productivity trends and coherence in productivity among

574   populations before and after 1990. These changes coincided with a major ocean regime shift,

575   ESA-listing, and other conservation efforts through the 1990s such as decreased hatchery

576   production, decreased harvest pressure, and increased investment in habitat conservation. We

577   acknowledge that less reliable survey methods, uncertainty in population-specific harvest rates,

578   and the relative influence of hatchery and harvest-related stressors prior to 1990 may have

579   influenced our findings; however, results from our study and others are indicative of a

580   mechanistic change point in productivity driven by conservation efforts and marine conditions.

581   Both of these factors have had widespread and measurable effects on salmon (Buhle et al. 2009,

582   Falcy and Suring 2018).

583   Spatial patterns of productivity became less variable during the post-1990 period and

584   tracked more closely with marine conditions during the second year of life. Increased coherence

585   in productivity generally signals that broad-scale (marine) drivers have a greater influence on

586   survival and fitness (Zimmerman et al. 2015, Ohlberger et al. 2016, Ruff et al. 2017), and

587   certainly productivity from 1990-on tracked closely with NPGO. This poses potential challenges

588   to conservation. Managers have little, if any, control over the ocean conditions that salmon

589 experience during their first marine year, and these conditions are becoming more complex with
590 climate change (Harley et al. 2006, Overland and Wang 2007, Di Lorenzo et al. 2010, Abdul-
591 Aziz et al. 2011). ESU-wide coupling also leads to a reduction in the population "portfolio
592 effect" such that marine conditions can be detrimental if temperature, prey availability, and other
593 factors that impact survival deteriorate for several years at a time (Schindler et al. 2010, Kilduff
594 et al. 2014, 2015). This was most recently observed with the high temperature "blob" off the
595 Pacific Coast of North America (Bond et al. 2015, Di Lorenzo and Mantua 2016). Conversely, a
596 direct relationship with environmental indicators such as NPGO may be helpful for managers if
597 they can integrate that information along with existing stock-recruitment data to more accurately
598 predict adult returns over the short-term (Rupp et al. 2012b, Burke et al. 2013, DeFilippo et al.
599 2021). Such forecasting methods are error prone in instances where the relationship between
600 productivity and the environment is inconsistent or decouples, as was the case for Oregon Coast
601 coho salmon starting around 2010.
602   We did not observe a strong relationship between productivity and freshwater rearing
603 conditions, but by no means are these conditions unimportant. For example, the Lakes
604 populations of coho salmon have declined almost continuously since the 1960s and this is likely
605 due to a variety of stressors in the lakes and their surrounding tributaries. Such stressors include
606 climactic shifts in temperature and precipitation, which we tested using the DFA models, or they
607 could be anthropogenic, like barriers to inland migration, eutrophication, and invasive species
608 (Sheer and Steel 2006, Mantua et al. 2010, Wainwright and Weitkamp 2013, Rubenson and
609 Olden 2020). These stressors are not unique to the Lakes stratum and may become more
610 impactful for other Oregon Coast coho populations, especially if marine conditions deteriorate.
611 Freshwater and estuarine habitat conditions are the lever by which managers influence
612 population productivity and resilience, and they are central to state and federal salmon recovery
613 plans (Lawson 1993, ODFW 2007, NMFS 2016). With respect to marine habitat conditions, the
614 relationship between NPGO and productivity appears to have decoupled to some extent over the
615 last decade. It is uncertain whether this is due to declining freshwater habitat quality for
616 spawning and juvenile rearing, conditions in the nearshore environment, or other environmental
617 variables that we did not measure. Within the Oregon Coast ESU, there are clearly opportunities
618 for robust and diverse management strategies to maximize life history diversity among
619 populations, taking advantage of the unique environmental attributes of coastal watersheds,

620 dendritic coastal lakes, and the Umpqua River basin. The greatest amount of benefit will occur

621 when managers work across multiple spatial scales to bolster productivity and survival

622 (Ohlberger et al. 2016, Ruff et al. 2017). Knowing if, and how, regional- and population-level

623 processes differ, and how they respond to specific environmental factors during freshwater and

624 marine rearing is an important step for managing salmon populations in rapidly changing

625 ecosystems.

626

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965 **Tables**

966 **Table 1.** Population characteristics for the 21 independent populations of Oregon Coast coho

967 salmon used in the dynamic factor analysis (DFA) including average recruitment (pre-harvest

968 adult returns, *R*), average total escapement (natural and hatchery produced fish, *S*), and average

969 percent of spawners that were hatchery fish (*H*). A "-" indicates missing data.

Population	Stratum	Data years	Watershed area (km²)	Pre-1990			Post-1990		
				R	S	H (%)	R	S	H (%)
Necanicum	NOR	1958 – 2016	216	2,518	1,310	38.00	1,559	1,537	15.70
Nehalem	NOR	1958 – 2016	2,215	28,251	11,338	15.63	12,680	12,664	20.37
Tillamook	NOR	1958 – 2016	1,455	12,743	5,229	30.81	6,054	5,612	16.48
Nestucca	NOR	1958 – 2016	826	11,359	4,639	17.00	3,385	2,833	5.56
Salmon	MID	1990 – 2016	193	-	-	-	696	1,237	58.63
Siletz	MID	1958 – 2016	955	3,821	1,908	36.94	7,379	6,656	15.96
Yaquina	MID	1958 – 2016	650	16,936	6,696	16.87	7,252	6,419	6.70
Beaver	MID	1958 – 1971, 1980 – 2016	87	2,638	1,255	18.11	2,060	1,877	3.52
Alsea	MID	1958 – 2016	1,222	6,850	3,350	37.56	7,843	7,193	15.56
Siuslaw	MID	1960 – 2016	2,008	29,250	9,246	2.47	15,068	13,832	10.04
Siltcoos	LAK	1960 – 2016	197	8,373	2,896	2.00	4,592	4,055	0.70
Tahkenitch	LAK	1960 – 2016	94	4,789	1,579	1.00	3,222	2,885	0.44
Tenmile	LAK	1958 – 2016	233	21,491	7,228	1.00	8,333	7,564	0.26
Lower Umpqua	UMP	1958 – 2016	1,838	16,489	5,262	1.25	11,711	9,824	3.04
Middle Umpqua	UMP	1958 – 2016	2,082	6,796	1,939	1.20	6,584	6,346	4.15
North Umpqua	UMP	1958 – 2016	3,558	2,041	1,410	23.69	3,083	5,820	48.70
South Umpqua	UMP	1958 – 2016	4,666	5,523	1,714	3.00	9,940	9,912	13.30
Coos	MSO	1958 – 2016	1,556	24,256	6,861	3.44	15,597	14,119	2.15
Coquille	MSO	1958 – 2016	2,739	25,335	8,225	8.38	15,776	13,937	1.74
Floras	MSO	1994 – 2016	330	-	-	-	2,682	2,712	3.83
Sixes	MSO	1990 – 2016	348	-	-	-	214	201	8.30

970

971 **Table 2.** Environmental covariates used in the dynamic factor analysis (DFA), time relative to

972 brood year each variable was expected to impact coho salmon, and source from which the data

973 set was derived.

Variable	Year	Source
Average summer air temperature (TEMP)	1	https://www.ncei.noaa.gov/access/search/data-search/global-summary-of-the-month
Average winter precipitation (PRECIP)	1	https://www.ncei.noaa.gov/access/search/data-search/global-summary-of-the-month
Pacific Decadal Oscillation (PDO)	2	https://psl.noaa.gov/data/climateindices/list
North Pacific Gyre Oscillation (NPGO)	2	http://www.o3d.org/npgo/

974

Table 3. Mean and standard deviation (SD) Pearson's correlation coefficients (*r*) calculated for
pre- and post-1990 time periods and within- and among-regional strata for Oregon Coast coho
salmon. NOR = North Coast, MID = Mid-Coast, LAK = Lakes, UMP = Umpqua River, and
MSO = Mid-South Coast.

Pre-1990			Post-1990		
Comp	**Mean**	**SD**	**Comp**	**Mean**	**SD**
Within	**0.46**	**0.22**	**Within**	**0.60**	**0.20**
NOR-NOR	0.50	0.17	NOR-NOR	0.74	0.08
MID-MID	0.40	0.27	MID-MID	0.60	0.17
LAK-LAK	0.40	0.18	LAK-LAK	0.60	0.07
UMP-UMP	0.59	0.17	UMP-UMP	0.71	0.14
MSO-MSO	0.28	-	MSO-MSO	0.36	0.25
Among	**0.26**	**0.24**	**Among**	**0.49**	**0.23**
MID-NOR	0.28	0.27	MID-NOR	0.62	0.15
LAK-NOR	0.27	0.19	LAK-NOR	0.40	0.15
LAK-MID	0.15	0.30	LAK-MID	0.35	0.23
UMP-NOR	0.42	0.13	UMP-NOR	0.60	0.15
UMP-MID	0.26	0.25	UMP-MID	0.58	0.16
UMP-LAK	0.21	0.11	UMP-LAK	0.38	0.17
MSO-NOR	0.27	0.26	MSO-NOR	0.44	0.34
MSO-MID	0.14	0.25	MSO-MID	0.45	0.27
MSO-LAK	0.27	0.23	MSO-LAK	0.37	0.23
MSO-UMP	0.28	0.24	MSO-UMP	0.54	0.23
TOTAL	**0.29**	**0.25**	**TOTAL**	**0.51**	**0.23**

Figure Legends

Figure 1. Conservation and management of the Oregon Coast coho salmon Evolutionarily Significant Unit (ESU) has shifted through time, including substantial reductions in harvest rates and hatchery production through the 1990s. Several policy actions have influenced how these populations are managed as well. In 1997, the Oregon Plan for Salmon and Watersheds was established by the Oregon State Legislature to restore native fish and their aquatic habitats. Soon after, in 1998 the Oregon Coast coho salmon ESU was listed as threatened under the Endangered Species Act (ESA; 16 U.S.C. §§ 1531–1544). These conservation efforts occurred concurrently with a change in survey methodology from index site sampling to a randomized survey design (vertical red line).

Figure 2. Map of independent populations of the Oregon Coast coho salmon Evolutionarily Significant Unit (ESU) and biogeographical strata.

Figure 3. Pearson's correlation coefficients (r) calculated among pairwise populations prior to 1990 (top) and from 1990-on (bottom) for Oregon Coast coho salmon. Black lines denote groupings within regional strata. NOR = North Coast, MID = Mid-Coast, LAK = Lakes, UMP = Umpqua River, and MSO = Mid-South Coast.

Figure 4. Pearson's correlation coefficient by distance between marine entry points for all pairwise comparisons of Oregon Coast coho salmon. Gray line indicates exponential decay trend, which exhibited a poor fit for the pre-1990 data and a marginal fit for the post-1990 data.

Figure 5. Modeled productivity trends and population loadings for the coast-wide dynamic factor analysis (DFA) of Oregon Coast coho salmon. NOR = North Coast, MID = Mid-Coast, LAK = Lakes, UMP = Umpqua River, and MSO = Mid-South Coast.

Figure 6. Modeled productivity trends and population loadings for pre-1990 regional DFAs. Black bars correspond with Trend 1 and gray bars correspond with Trend 2.

1011 **Figure 7.** Modeled productivity trends and population loadings for post-1990 regional dynamic
1012 factor analyses (DFAs) of Oregon Coast coho salmon. Black bars correspond with Trend 1 and
1013 gray bars correspond with Trend 2. Plotted values are means, dashed lines are 95% confidence
1014 intervals. NOR = North Coast, MID = Mid-Coast, LAK = Lakes, UMP = Umpqua River, and
1015 MSO = Mid-South Coast.
1016
1017 **Figure 8.** Predicted productivity trends for the North- (NOR), Mid- (MID), Umpqua (UMP;
1018 Trend 1), and Mid-South Coast (MSO) strata of Oregon Coast coho salmon overlaid with z-
1019 transformed Pacific Decadal Oscillation (PDO; top) and North Pacific Gyre Oscillation (NPGO;
1020 bottom). These trends demonstrated a significant ($P < 0.05$) correlation with marine drivers.
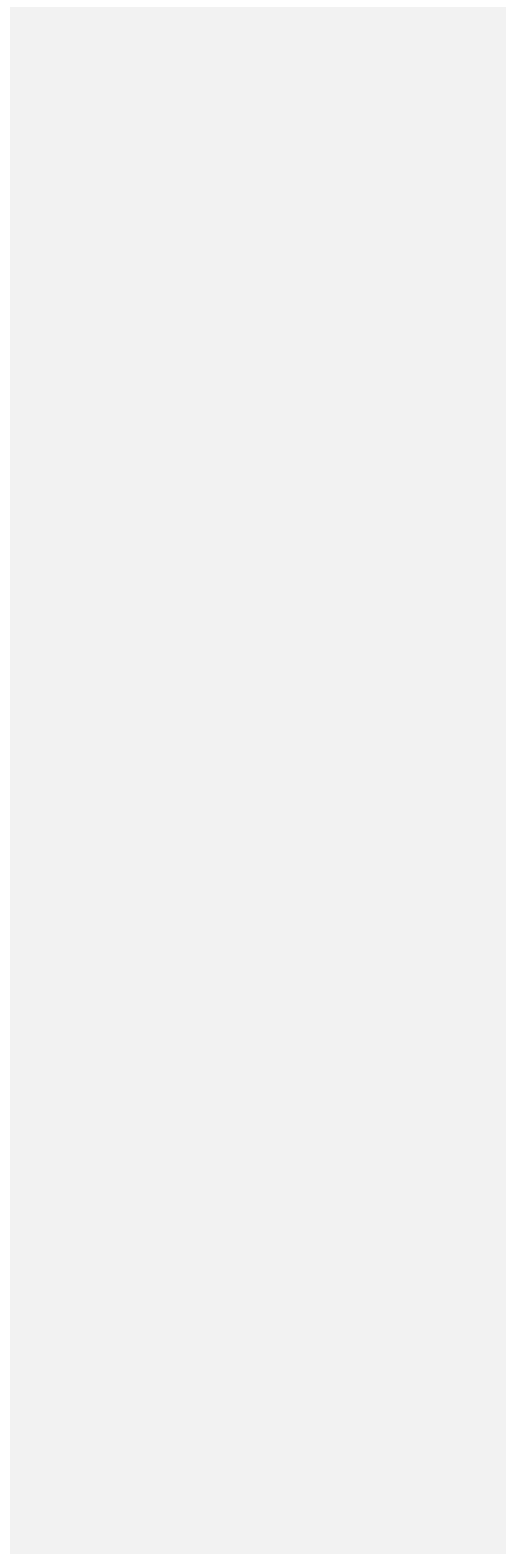
1021   **Figure 1**

1022

1023 **Figure 2**
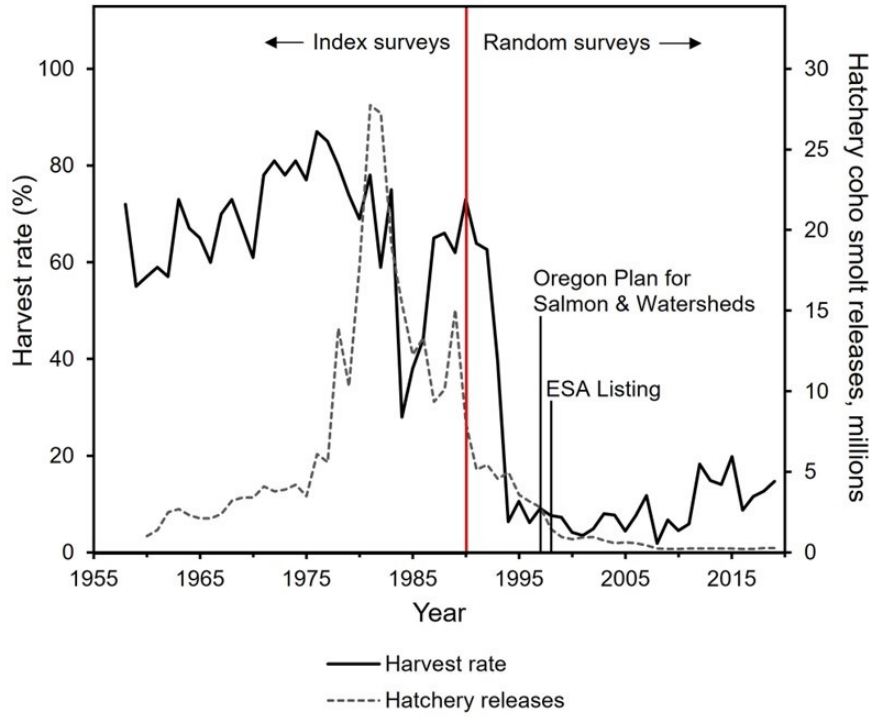
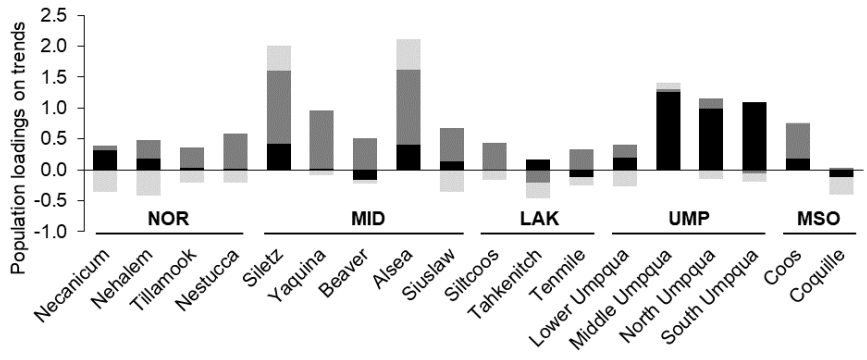1024

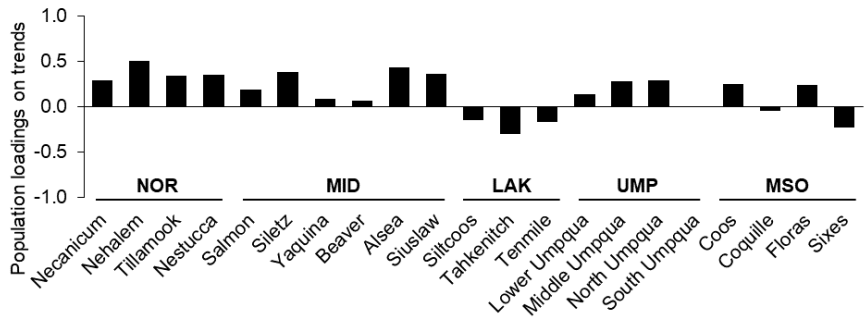**Figure 3**
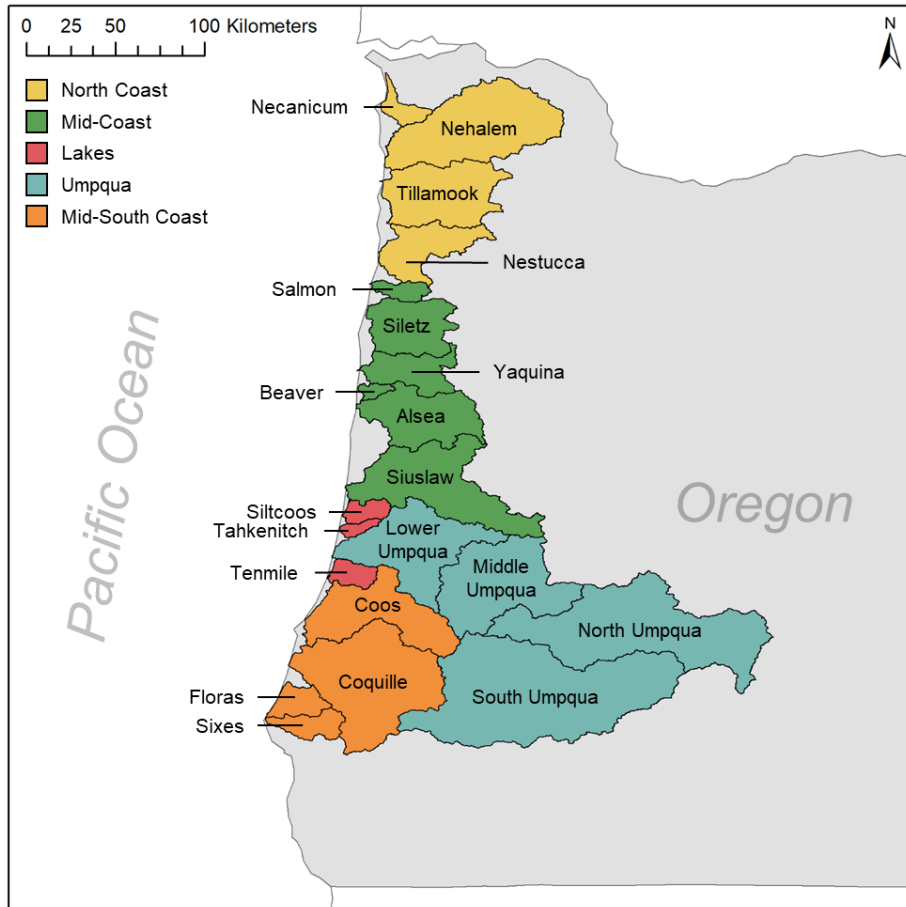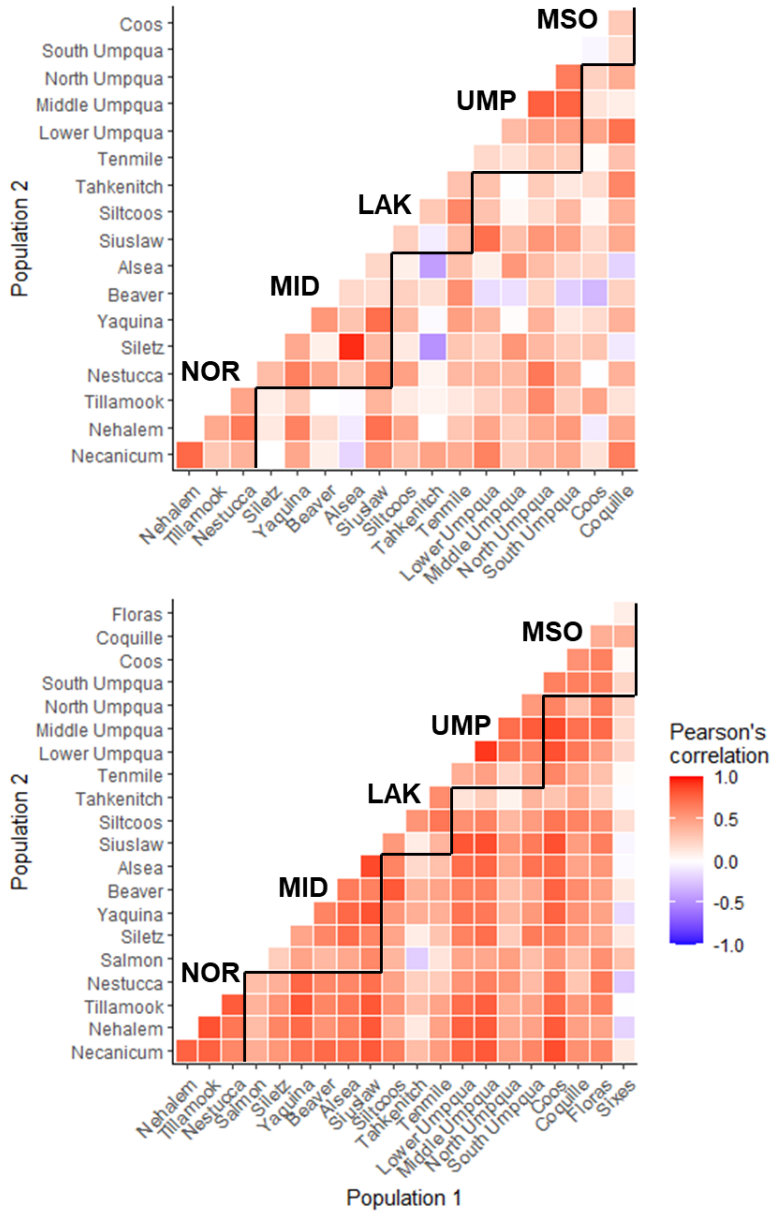
1027   **Figure 4**
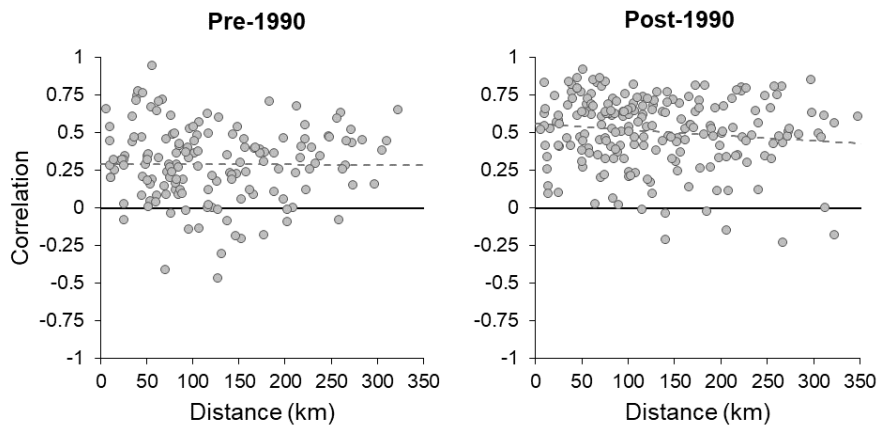
Pre-1990 / Post-1990

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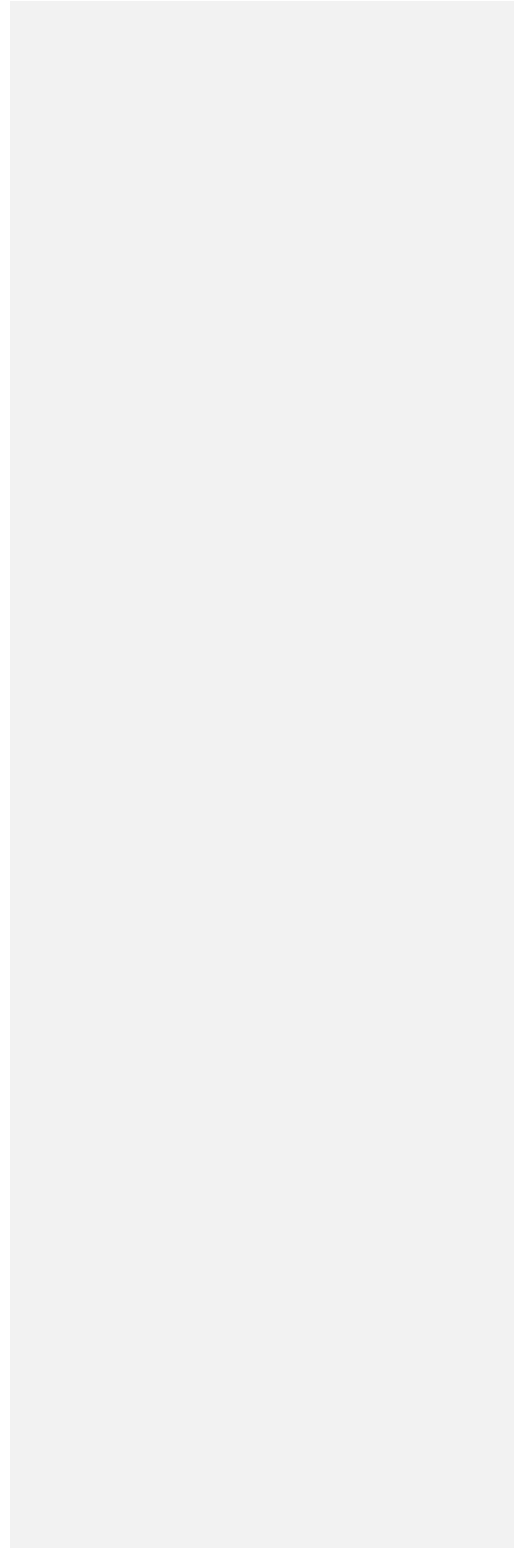
1029   **Figure 5**

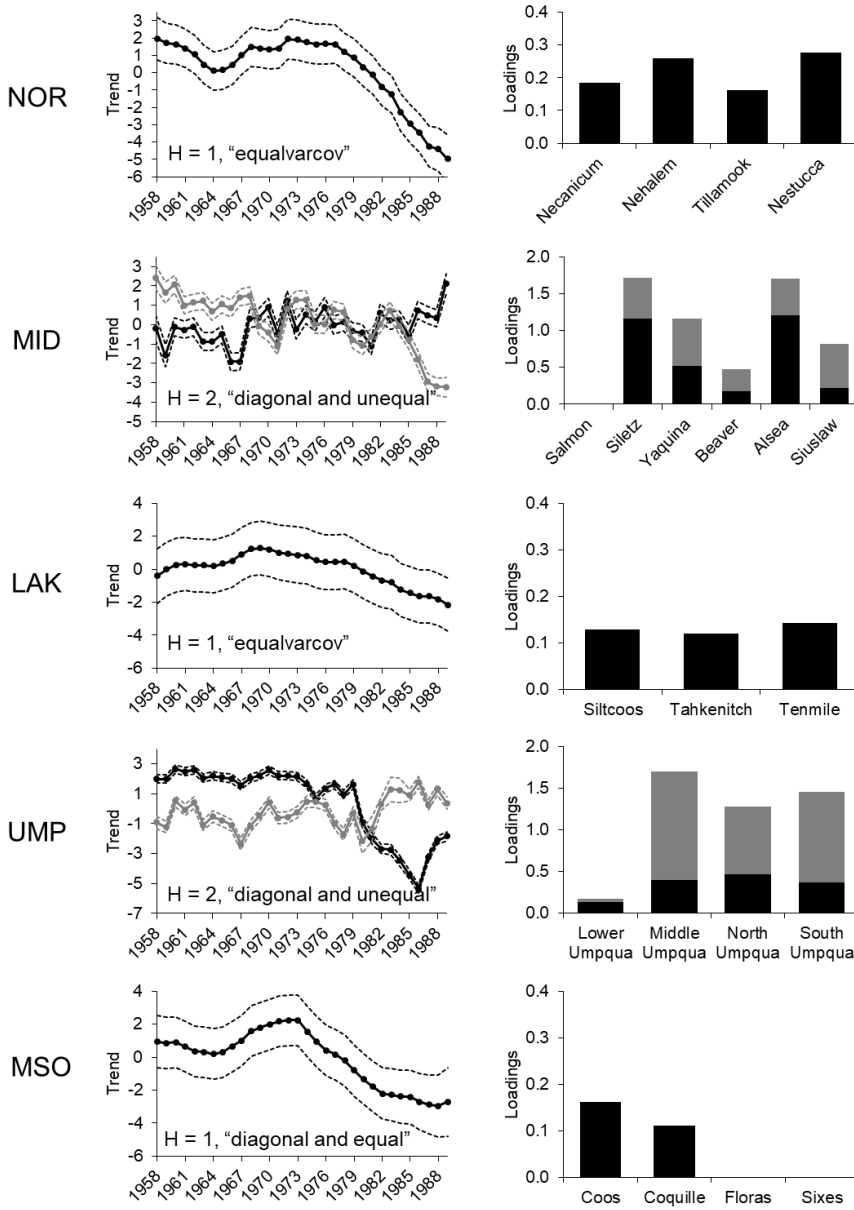**Pre-1990**

Post-1990
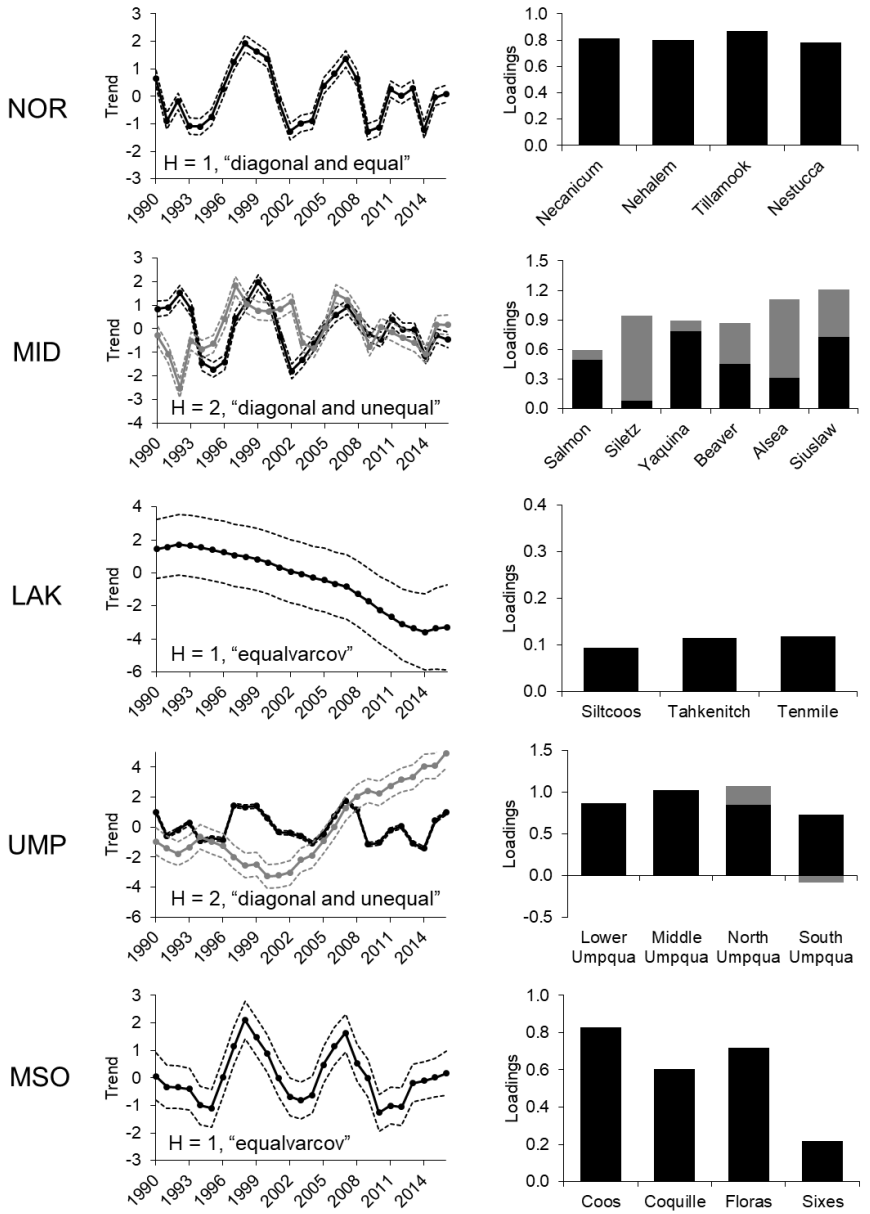

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Figure 6
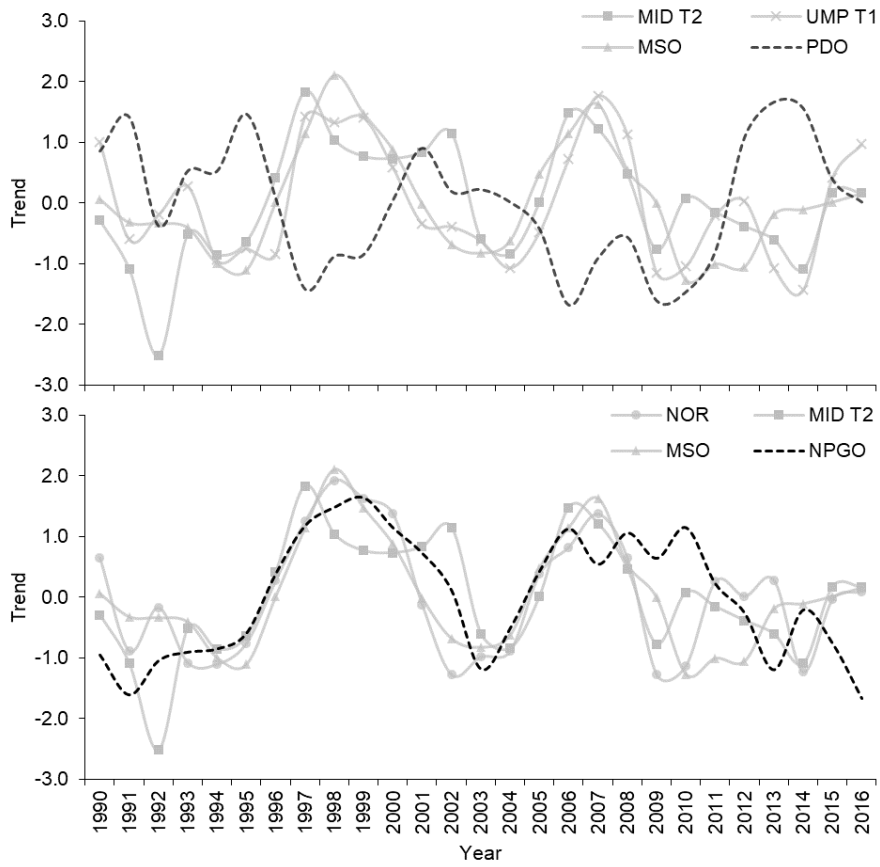
1033   **Figure 7**

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1035   **Figure 8**

1036