**Supplementary Information Text**

**1. Methods for compound specific stable isotope analysis**

Collagen samples have been analyzed for both CSSIA and bulk δ15N which require 10 mg of purified collagen (100 mg of bone). Preliminary analyses were conducted to determine the highest rate of collagen return from bone sampled from different parts of the skull to minimize destruction. Samples were taken from the internal occipital shelf to maintain external integrity. Laboratory preparation occurred in the Holgrieve Ecosystem Ecology Lab at University of Washington. Bone was decalcified using 0.2 M HCl for 24-72 hours depending on bone thickness, followed by centrifugation and nanopure water rinse. Removal of humic acids was conducted using 0.125 M NaOH for 20 hours. Samples were washed to a neutral pH, then solubilized in 0.01N HCl. Once solubilized samples were blown down under N2 to prevent isotopic fractionation, and freeze dried. Freeze dried collagen was be analyzed for bulk isotopic composition of nitrogen by the UW IsoLab (isolab.ess.washington.edu) using a coupled elemental analyzer-isotope ratio mass spectrometer following the standard protocols of the laboratory. C:N ratios were calculated from this data, which is a measure of the quality for carbon and nitrogen analyses of bone collagen for isotopic analysis. Only three observations were outside of the acceptable rang of 2.7-3.6; indicating there was no substantial loss of glycine or addition of nitrogen due to microbial processing from mortality, decay, curation, and analysis.

δ15N of eleven amino acids[[1]](#footnote-1) were measured in the new UW Facility for Compound-Specific Isotope Analysis of Environmental Samples. Samples were prepared following the procedures developed by Popp Marine Lab at University of Hawaii Manoa. Briefly, proteins were hydrolyzed in 6N HCl and purified using a cation exchange column. Amino acids were esterified using isopropanol acetyl chloride, and derivatized via acylation with 4:1 toluene: pivaloyl chloride. Samples were brought up in ethyl acetate and analyzed using a coupled gas chromatography-combustion-isotope ratio mass spectrometer system (GC-C-irMA; Thermo Scientific Trace GC + GC IsoLink coupled to a Delta V irMS) in continuous flow mode monitoring masses (m/z) 28 and 29 using a db-35 column. For each run a 12 amino acid external standard with known isotopic composition was injected three times followed by sample injections. Samples were injected in triplicate, with the 12 amino acid standard injected every two samples (or six injections). A two-hour column oxidation was performed after 6 samples(25 injections). Samples and standards included norleucine as an internal standard.

For each machine run, a linear model was fit for each individual amino acid using the following equation:

Where m represents the slope of the precision drift, t represents the injection number since last column oxidation, and Std represents the δ15N of an individual amino acid for a standard observation. The data was then corrected using the following equations:

Where Daa,t is the difference between an observed standard δ15N (Stdaa,t) for a given amino acid at a given injection number and the true δ15N for that standard. Then:

Where the drift value, Daa,t, is subtracted from the sample value for a given aa and a given injection to correct the observed sample values for precision drift since last column oxidation. Mean sample corrected values for the triplicate injections were used for all amino acid δ15N.

**2. Methods for dynamic factor analysis**

To reduce collinearity among environmental variables and limit the number of models tested, datasets were categorized *a priori* into four main mechanistic processes: climatic condition, surface mixing, sea surface temperature, and upwelling. To reduce the dimensionality of the data associated with each process we used fit a dynamic factor analysis (DFA) model to time series from each driver category to estimate a latent trend (Appendices 1 - 3). DFA is a dimension reduction technique that identifies common processes underlying a set of time series. The underlying model in DFA treats observed data as linear combinations of latent unobservable "trends" which are modeled as a random walk (Zuur et al. 2003). Latent variables are weighted based on the portion of temporal variation they explain taking the following form:

where δ15Nsource, and additional environmental variables (Table 1-3) were natural log transformed and then standardized.The observed data **y*t*** are modeled as combinations of latent trends **x**t at time *t* (the dimensions of  **x**tmatching the number of states) and factor loadings (**Z**) at time *t*, in addition to optional covariates (observed variables **d**t and estimated coefficients **D**) plus random observation error (**vt**) which are multivariate normal . DFA is commonly applied to multivariate time series problems in fisheries and ecology and has been used to identify patterns of oceanographic variability that drive Pacific salmon stocks (Stachura et al. 2014), and environmental drivers and stock structure of Chinook salmon (Jorgenson et al. 2016, Ohlbereger et al. 2016). Often, a question of DFA is to identify how many latent trends are supported for a particular dataset, and model selection methods are used to compare alternative model structures. Because we were interested in using DFA to generate indices of the environmental data, however, we limited the scope of our DFA models to just having one latent trend. We fit one DFA to the climatic drivers (which are shared across regions) and separate region-specific DFAs to data for sea surface temperature, upwelling, and surface mixing.

**3. Methods for Multivariate Autoregressive State-Space (MARSS) Model**

A MARSS model was fit to herring stock spawning biomass and harbor seal stock population size. Harbor seal datasets and herring biomass were collected by stock (n = 7 and n = 20, respectively) but did not have observations for every for every year (Figure S1 and Figure S2). In order to get total population and total biomass estimates for these species for each year two MARSS models were fit to the data, one for each species, to estimate population and biomass for each year for each for each stock. For both datasets process variance (Q) assumed equal variance and covariance across stocks, and observation error (R) was assumed to be equal across stocks. U and x0 were both set to unequal, thus assuming they vary across stocks. Model states (Figure S3 and S4) were summed across years for total biomass/population size estimates. Harbor seal data has not been collected since 2000 and we assumed the population has remained constant from 2000-2010.

**SI References**

Boyin Huang, Peter W. Thorne, Viva F. Banzon, Tim Boyer, Gennady Chepurin, Jay H. Lawrimore, Matthew J. Menne, Thomas M. Smith, Russell S. Vose, and Huai-Min Zhang (2017): NOAA Extended Reconstructed Sea Surface Temperature (ERSST), Version 5. NOAA National Centers for Environmental Information. doi:10.7289/V5T72FNM

Di Lorenzo E., Schneider N., Cobb K. M., Chhak, K, Franks P. J. S., Miller A. J., McWilliams J. C., Bograd S. J., Arango H., Curchister E., Powell T. M. and P. Rivere, 2008: North Pacific Gyre Oscillation links ocean climate and ecosystem change. Geophys. Res. Lett., 35, L08607, doi:10.1029/2007GL032838

**Table S1:** Covariates used to test ocean condition as a bottom-up driver of harbor seal trophic ecology. Total number of models tested = 53.

|  |  |  |  |
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|  | Time Series Description | Length | Source |
| Discharge | Total discharge from the Columbia River at Dalles, WA during summer months of high discharge (May-Oct) from monthly U.S. Geological Survey discharge data. | 1879-2018 | Data Source: [USGS 14105700](https://waterdata.usgs.gov/nwis/uv?site_no=14105700) |
| Sea Surface Temperature (SST) | Average of monthly NOAA Extended Reconstructed SST for summer (Jul-Sep) in coastal Washington (48°N, 125°W). | 1854-2019 | Data Source: [NOAA ERSST V5](https://www.esrl.noaa.gov/psd/data/gridded/data.noaa.ersst.v5.html)  SST data was obtained from NOAA\_ERSST\_V5 data provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at https://www.esrl.noaa.gov/psd/ (Huang et al. 2017). |
| Upwelling | Mean coastal upwelling index (CUI) coastal Washington (45°N, 125°W) using Bakun upwelling calculation based on Ekman's theory of mass transport due to wind stress, for spring (Apr-Jun). | 1946-2019. | Data Source: [NOAA ERD SWFSC](https://oceanview.pfeg.noaa.gov/products/upwelling/dnld) |
| North Pacific Gyre Oscillation | 2nd dominant mode of sea surface height variability in the northeast Pacific. Correlates with fluctuations in salinity nutrients and chlorophyll-a. | 1950-2019 | Data Source: Di Lorenzo et al. 2008. [NPGO](http://www.o3d.org/npgo/) |
| Multivariate ENSO Index | The extended Multivariate ENSO Index (MEI) uses Principle Component analysis on six variables: sea-level pressure, u and v component of the surface wind vector, sea surface temperature and cloudiness fraction in the tropical Pacific. | 1950-2019 | Data Source: NOAA/ESRL (https://psl.noaa.gov/enso/mei.ext/table.ext.html) via California Current Integrated Ecosystem Assessment [MEI](https://www.integratedecosystemassessment.noaa.gov/regions/california-current/cc-indicator-climate-ocean-drivers) |
| Pacific Decadal Oscillation | Same as eastern Bering Sea | 1900--2018 | Data Sources: [PDO](http://research.jisao.washington.edu/pdo/PDO.latest.txt); Zhang et al. 1997; Mantua et al 1997 |

**Table S2:** Covariates used to test prey availability as a bottom-up driver of harbor seal trophic ecology. Total number of models tested = 59.

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| --- | --- | --- | --- |
|  | Time Series Description | Length | Source |
| Herring Biomass | Adult herring spawning biomass from egg deposition surveys for the estimated from Washington State Department of Fish and wildlife by Siple and Francis 2015. | 1973-2012 | Siple, M.C. and T.B. Francis. 2015. Population diversity in Pacific herring of the Puget Sound, USA. |
| Hake Biomass | Pacific Hake (whiting) relative spawning biomass in US and Canadian waters. | 1973-2012 | Berger et al. 2017. Table 8 total spawning biomass. |
| Chinook Salmon Spawners | Chinook salmon spawner summary data including all populations with a time series with data from at least 1973. Includes: Cedar River, Coweeman River, Elochoman River, Grays and Chinook Rivers, Green River, Kalama River, Lewis River, Lower Cowlitz River, Lower and Upper Sauk River, Lower and Upper Skagit River, McKenzie River, Mid-Hood Canal, Nisqually River, Puyallup River, Skokomish River, Skykomish River, Snoqualmie River, Suiattle River, Toutle River, Upper Gorge Tributaries, White River and White Salmon River. | 1973-2012 | Northwest Fisheries Science Center, 2020: SPS Abundance - Salmon spawner abundance data compilation and database management, [https://www.webapps.nwfsc.noaa.gov/apex/f?p=261:1:::NO::P1\_ARCHIVE\_NOTE\_CHECK:1&cs=1A0A1845C9A3C7202FD5C2934C6FD9410#](https://www.webapps.nwfsc.noaa.gov/apex/f?p=261:1:::NO::P1_ARCHIVE_NOTE_CHECK:1&cs=1A0A1845C9A3C7202FD5C2934C6FD9410) |
| Smolts | Hatchery release data from the Regional Mark Information System and Wild Salmon Production data summarized by Chasco et al. 2017. Data was summed across both datasets for total juvenile salmon production. | 1973-2012 | RMIS: https://www.rmis.org//rmis\_login.php?action=Login&system=cwt  Summarized: https://github.com/bchasco/COAST\_WIDE |
| Coho Salmon | Coho salmon spawner summary data including all populations with a time series with data from at least 1973. Includes: Coastal Estuaries, Eastern Bays, Hood Canal, Olympic Peninsula, Puget Sound, San Juan Islands, Strait of Juan de Fuca. | 1973-2012 | Northwest Fisheries Science Center, 2020: SPS Abundance - Salmon spawner abundance data compilation and database management |
| Chum Salmon | Chum salmon spawner summary data including all populations with a time series with data from at least 1973. Includes: Hood Canal, Strait of Juan de Fuca. | 1973-2012 | Northwest Fisheries Science Center, 2020: SPS Abundance - Salmon spawner abundance data compilation and database management |
| Harbor Seal Abundance | Harbor seal population estimates based on coastal estuary, eastern Bays, Hood Canal, Olympic Peninsula, Puget Sound, San Juan Islands, and the Strait of Juan de Fuca counts. | 1975-2012 | Jeffries, S., H. Huber, J. Calambokidis and J. Laake. 2003. Trends and status of harbor seals in Washington state: 1978-1999. The Journal of Wildlife Management 67: 207-218. |

**Table S3:** Covariates used to test productivity as a bottom-up driver of harbor seal trophic ecology. Total number of models tested = 5.

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| --- | --- | --- | --- |
|  | Time Series Description | Length | Source |
| δ15N | Food web assimilated nitrogen signature related to changes in nitrogen availability and resources | 1928-2014 | Data Source: Feddern et al. 2020 |
| δ13C | Carbon isotope signature is associated with changes in phytoplankton community composition and growth rates. | 1928-2014 | Data Source: Feddern et al. 2020 |

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| Amino Acid | Mean Precision |
| Phenylalanine | 0.90 |
| Glutamic Acid | 1.0 |
| Alanine | 0.84 |
| Proline | 1.4 |
| Valine | 1.0 |

**Figure S1**: Analysis of a) δ15NSource and b) δ13C by month. For both models, there was no significant slope (p>0.1)

**Figure S2**: Analysis of a) δ15NSource and b) δ13C by month. For both models, s(month) p>0.1 indicating no seasonality of harbor seal bone collagen stable isotope signature.



**Figure S3**: Residuals for the model with the most support plotted by year.



**Figure S4:** Model residual plots for the model with the most support from the candidate model set described in Table S3.

1. Alanine, glycine, proline, aspartic acid, leucine, isoleucine, valine, threonine, serine, glutamic acid, phenylalanine [↑](#footnote-ref-1)