

Technical Documentation, State of the Ecosystem Report

Northeast Fisheries Science Center

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Introduction

The purpose of this document is to collate the methods used to access, collect, process, and analyze derived data (“indicators”) used to describe the status and trend of social, economical, ecological, and biological conditions in the Northeast Shelf Large Marine Ecosystem (see figure, below). These indicators are further synthesized in State of the Ecosystem Reports produced annually by the Northeast Fisheries Science Center for the New England Fisheries Management Council and the Mid-Atlantic Fisheries Management Council. The metadata for each indicator (in accordance with the Public Access to Research Results (PARR) directive) and the methods used to construct each indicator are described in the subsequent chapters, with each chapter title corresponding to an indicator or analysis present in State of the Ecosystem Reports. The most recent and usable html version of this document can be found at the NOAA EDAB Github. The PDF version of this document is for archiving only.

Indicators included in this document were selected to clearly align with management objectives, which is required for integrated ecosystem assessment (Levin et al. 2009), and has been advised many times in the literature (Degnbol and Jarre 2004; Jennings 2005; Rice and Rochet 2005; Link 2005). A difficulty with practical implementation of this in ecosystem reporting can be the lack of clearly specified ecosystem-level management objectives (although some have been suggested (Murawski 2000)). In our case, considerable effort had already been applied to derive both general goals and operational objectives from both US legislation such as the Magnuson-Stevens Fisheries Conservation and Management Act (MSA) and regional sources (DePiper et al. 2017). These objectives are somewhat general and would need refinement together with managers and stakeholders, however, they serve as a useful starting point to structure ecosystem reporting.

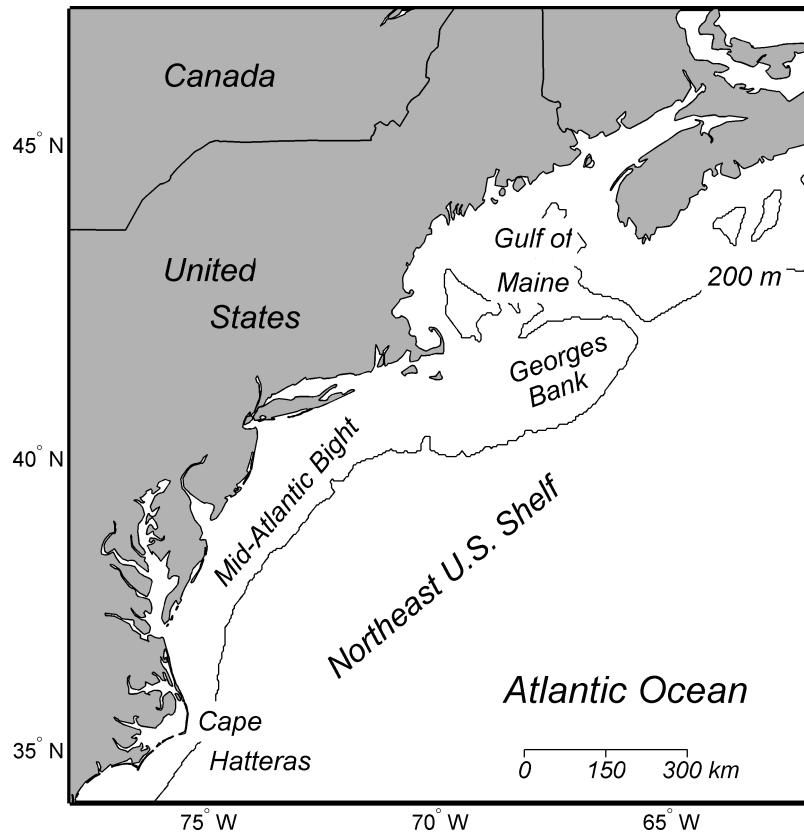


Figure 1: Map of Northeast U.S. Continental Shelf Large Marine Ecosystem from Hare et al. (2016).

Chapter 1

Data and Code Access

1.0.1 About

The Technical Documentation for the State of the Ecosystem (SOE) reports is a bookdown document; hosted on the NOAA Northeast Fisheries Science Center (NEFSC) Ecosystems Dynamics and Assessment Branch Github page, and developed in R. Derived data used to populate figures in this document are queried directly from the ecodata R package or the NEFSC ERDDAP server. ERDDAP queries are made using the R package `rerddap`.

1.0.2 Accessing data and build code

In this technical documentation, we hope to shine a light on the processing and analytical steps involved to get from source data to final product. This means that whenever possible, we have included the code involved in source data extraction, processing, and analyses. We have also attempted to thoroughly describe all methods in place of or in supplement to provided code. Example plotting code for each indicator is presented in sections titled “Plotting”, and these code chunks can be used to recreate the figures found in ecosystem reporting documents where each respective indicator was included¹.

Source data for the derived indicators in this document are linked to in the text unless there are privacy concerns involved. In that case, it may be possible to access source data by reaching out to the Point of Contact associated with that data set. Derived data sets make up the majority of the indicators presented in ecosystem reporting documents, and these data sets are available for download through the ecodata R package.

1.0.3 Building the document

Start a local build of the SOE bookdown document by first cloning the project’s associated git repository. Next, if you would like to build a past version of the document, use `git checkout [version_commit_hash]` to revert the project to a past commit of interest, and set `build_latest <- FALSE` in this code chunk. This will ensure the project builds from a cached data set, and not the most updated versions present on the NEFSC ERDDAP server. Once the `tech-doc.Rproj` file is opened in RStudio, run `bookdown::serve_book()` from the console to build the document.

¹There are multiple R scripts sourced throughout this document in an attempt to keep code concise. These scripts include `BasePlot_source.R`, `GIS_source.R`, and `get_erdap.R`. The scripts `BasePlot_source.R` and `GIS_source.R` refer to deprecated code used prior to the 2019 State of the Ecosystem reports. Indicators that were not included in reports after 2018 make use of this syntax, whereas newer indicators typically use `ggplot2` for plotting.

1.0.3.1 A note on data structures

The majority of the derived time series used in State of the Ecosystem reports are in long format. This approach was taken so that all disparate data sets could be “bound” together for ease of use in our base plotting functions.

Chapter 2

Aggregate Groups

Description: Mappings of species into aggregate group categories for different analyses

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018, 2019, 2020), State of the Ecosystem - Mid-Atlantic (2018, 2019, 2020)

Indicator category: Synthesis of published information

Contributor(s): Geret DePiper, Sarah Gaichas, Sean Hardison, Sean Lucey

Data steward: Sean Lucey Sean.Lucey@noaa.gov

Point of contact: Sean Lucey Sean.Lucey@noaa.gov

Public availability statement: Source data is available to the public (see Data Sources).

2.1 Methods

The State of the Ecosystem (SOE) reports are delivered to the New England Fishery Management Council (NEFMC) and Mid-Atlantic Fishery Management Council (MAFMC) to provide ecosystems context. To better understand that broader ecosystem context, many of the indicators are reported at an aggregate level rather than at a single species level. Species were assigned to an aggregate group following the classification scheme of Garrison and Link (2000) and Link et al. (2006). Both works classified species into feeding guilds based on food habits data collected at the Northeast Fisheries Science Center (NEFSC). In 2017, the SOE used seven specific feeding guilds (plus an “other” category; Table 2.1). These seven were the same guilds used in Garrison and Link (2000), which also distinguished ontogenetic shifts in species diets.

For the purposes of the SOE, species were only assigned to one category based on the most prevalent size available to commercial fisheries. However, several of those categories were confusing to the management councils, so in 2018 those categories were simplified to five (plus “other”; Table 2.2) along the lines of Link et al. (2006). In addition to feeding guilds, species managed by the councils have been identified. This is done to show the breadth of what a given council is responsible for within the broader ecosystem context.

In the 2020 report, squids were moved from planktivores to piscivores.

2.1.1 Data sources

In order to match aggregate groups with various data sources, a look-up table was generated which includes species’ common names (COMNAME) along with their scientific names (SCINAME) and several species codes. SVSPP codes are used by the NEFSC Ecosystems Surveys Branch (ESB) in their fishery-independent Survey

Table 2.1: Aggregate groups use in 2017 SOE. Classifications are based on @garrison2000dietary .

Feeding.Guild	Description
Apex Predator	Top of the food chain
Piscivore	Fish eaters
Macrozoo-piscivore	Shrimp and small fish eaters
Macroplanktivore	Amphipod and shrimp eaters
Mesoplanktivore	Zooplankton eaters
Benthivore	Bottom eaters
Benthos	Things that live on the bottom
Other	Things not classified above

Table 2.2: Aggregate groups use in 2018 SOE. Classifications are based on @link2006EMAX.

Feeding.Guild	Description
Apex Predator	Top of the food chain
Piscivore	Fish eaters
Planktivore	Zooplankton eaters
Benthivore	Bottom eaters
Benthos	Things that live on the bottom
Other	Things not classified above

Database (SVDBS), while NESPP3 codes refer to the codes used by the Commercial Fisheries Database System (CFDBS) for fishery-dependent data. A third species code provided is the ITIISPP, which refers to species identifiers used by the Integrated Taxonomic Information System (ITIS). Digits within ITIS codes are hierarchical, with different positions in the identifier referring to higher or lower taxonomic levels. More information about the SVDBS, CFDBS, and ITIS species codes are available in the links provided below.

Management responsibilities for different species are listed under the column “Fed.managed” (NEFMC, MAFMC, or JOINT for jointly managed species). More information about these species is available on the FMC websites listed below. Species groupings listed in the “NEIEA” column were developed for presentation on the Northeast Integrated Ecosystem Assessment (NE-IEA) website. These groupings are based on EMAX groupings (Link et al. 2006), but were adjusted based on conceptual models developed for the NE-IEA program that highlight focal components in the Northeast Large Marine Ecosystem (i.e. those components with the largest potential for perturbing ecosystem dynamics). NE-IEA groupings were further simplified to allow for effective communication through the NE-IEA website.

2.1.1.1 Supplemental information

See the following links for more information regarding the NEFSC ESB Bottom Trawl Survey, CFDBS, and ITIS:

- <https://www.itis.gov/>
- <https://import.nmfs.noaa.gov/import/item/22561>
- <https://import.nmfs.noaa.gov/import/item/22560>
- <https://import.nmfs.noaa.gov/import/item/27401>

More information about the NE-IEA program is available [here](#).

More information about the New England Fisheries Management Council is available [here](#).

More information about the Mid-Atlantic Fisheries Management Council is available [here](#).

2.1.2 Data extraction

Species lists are pulled from SVDBS and CFDBS. They are merged using the ITIS code. Classifications from Garrison and Link (Garrison and Link 2000) and Link et al. (Link et al. 2006) are added manually. The R code used in the extraction process can be found [here](#).

Chapter 3

Annual SST Cycles

Description: Annual SST Cycles

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018), State of the Ecosystem - Mid-Atlantic (2018)

Indicator category: Database pull with analysis

Contributor(s): Sean Hardison, Vincent Saba

Data steward: Kimberly Bastille, kimberly.bastille@noaa.gov

Point of contact: Kimberly Bastille, kimberly.bastille@noaa.gov

Public availability statement: Source data are available here.

3.1 Methods

3.1.1 Data sources

Data for annual sea surface temperature (SST) cycles were derived from the NOAA optimum interpolation sea surface temperature (OISST) high resolution dataset (NOAA OISST V2 dataset) provided by NOAA's Earth System Research Laboratory's Physical Sciences Devision, Boulder, CO. The data extend from 1981 to present, and provide a $0.25^\circ \times 0.25^\circ$ global grid of SST measurements (Reynolds et al. 2007). Gridded SST data were masked according to the extent of Ecological Production Units (EPU) in the Northeast Large Marine Ecosystem (NE-LME) (See "EPU_Extended" shapefiles).

3.1.2 Data extraction

Daily mean sea surface temperature data for 2017 and for each year during the period of 1981-2012 were downloaded from the NOAA OI SST V2 site to derive the long-term climatological mean for the period. The use of a 30-year climatological reference period is a standard procedure for metereological observing (WMO 2017). These reference periods serve as benchmarks for comparing current or recent observations, and for the development of standard anomaly data sets. The reference period of 1982-2012 was chosen to be consistent with previous versions of the State of the Ecosystem report.

R code used in extraction and processing can be found [here](#)

3.1.3 Data analysis

We calculated the long-term mean and standard deviation of SST over the period of 1982-2012 for each EPU, as well as the daily mean for 2017.

R code used for analysis and plotting can be found [here](#)

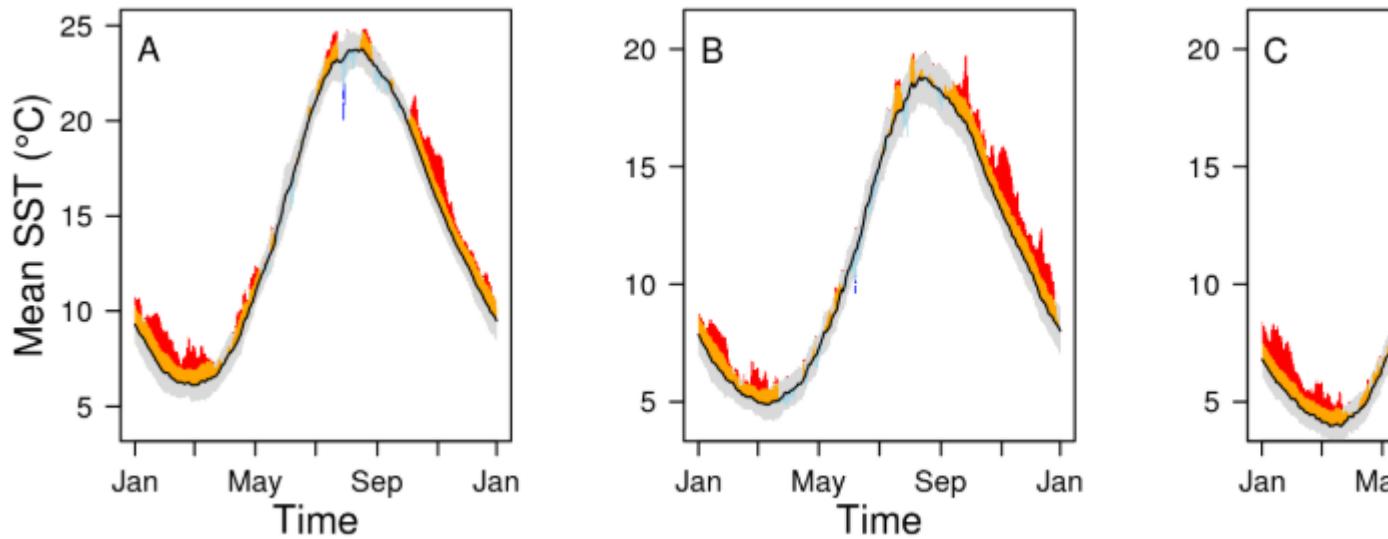


Figure 3.1: Long-term mean SSTs for the Mid-Atlantic Bight (A), Georges Bank (B), and Gulf of Maine (C). Orange and cyan shading show where the 2017 daily SST values were above or below the long-term mean respectively; red and dark blue shades indicate days when the 2017 mean exceeded ± 1 standard deviation from the long-term mean.

Chapter 4

Aquaculture

Description: Aquaculture indicators

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2017, 2018), State of the Ecosystem - Mid-Atlantic (2017, 2018, 2019)

Indicator category: Synthesis of published information

Contributor(s): Sean Hardison, Lisa Calvo, Karl Roscher

Data steward: Kimberly Bastille kimberly.bastille@noaa.gov

Point of contact: Kimberly Bastille kimberly.bastille@noaa.gov

Public availability statement: Source data are publicly available in referenced reports, and are also available for download [here](#).

4.1 Methods

Aquaculture data included in the State of the Ecosystem (SOE) report were time series of number of oysters sold in Virginia, Maryland, and New Jersey.

4.1.1 Data sources

Virginia oyster harvest data are collected from mail and internet-based surveys of active oyster aquaculture operations on both sides of the Chesapeake Bay, which are then synthesized in an annual report (Hudson 2017). In Maryland, shellfish aquaculturists are required to report their monthly harvests to the Maryland Department of Natural Resources (MD-DNR). The MD-DNR then aggregates the harvest data for release in the Maryland Aquaculture Coordinating Council Annual Report (ACC 2017), from which data were collected. Similar to Virginia, New Jersey releases annual reports synthesizing electronic survey results from lease-holding shellfish growers. Data from New Jersey reflects cage reared oysters grown from hatchery seed (Calvo 2017).

4.1.2 Data extraction

Data were collected directly from state aquaculture reports. Oyster harvest data in MD was reported in bushels which were then converted to individual oysters by an estimate of 300 oysters bushel⁻¹. View processing code for this indicator [here](#).

4.1.3 Data analysis

No data analyses occurred for this indicator.

4.1.4 Data processing

Aquaculture data were formatted for inclusion in the `ecodata` R package using the code found [here](#).

4.1.5 Plotting

Code for plotting data included in the State of the Ecosystem report can be found [here](#).

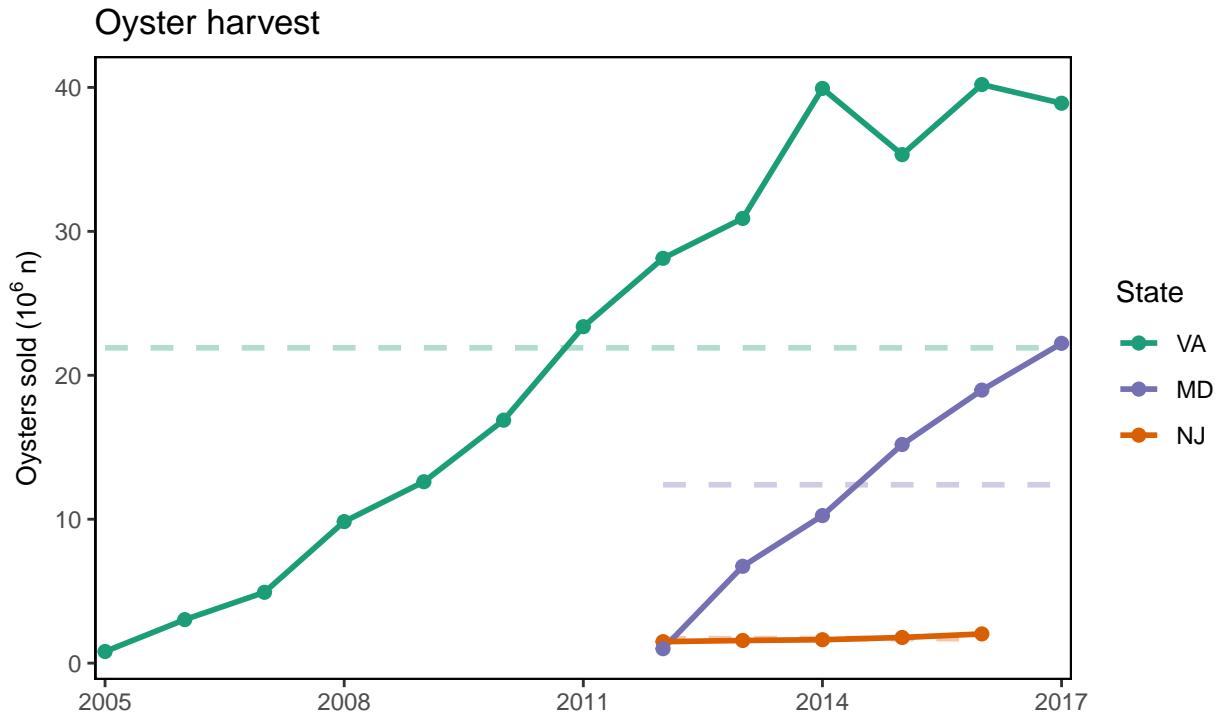


Figure 4.1: Oyster aquaculture production in terms of number of oysters sold from Virginia, Maryland, and New Jersey.

Chapter 5

Bennet Indicator

Description: Bennet Indicator

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018, 2019, 2020), State of the Ecosystem - Mid-Atlantic (2018, 2019, 2020)

Indicator category: Database pull with analysis

Contributor(s): John Walden

Data steward: Kimberly Bastille, kimberly.bastille@noaa.gov

Point of contact: John Walden, john.walden@noaa.gov

Public availability statement: Derived CFDBS data are available for this analysis (see Comland).

5.1 Methods

5.1.1 Data sources

Data used in the Bennet Indicator were derived from the Comland data set; a processed subset of the Commercial Fisheries Database System (CFDBS). The derived Comland data set is available for download here.

5.1.2 Data extraction

For information regarding processing of CFDBS, please see Comland methods. The Comland dataset containing seafood landings data was subsetted to US landings after 1964 where revenue was ≥ 0 for each Ecological Production Unit (i.e. Mid-Atlantic Bight, Georges Bank, and Gulf of Maine). Each EPU was run in an individual R script, and the code specific to Georges Bank is shown [here](.).

5.1.3 Data analysis

Revenue earned by harvesting resources from a Large Marine Ecosystem (LME) at time t is a function of both the quantity landed of each species and the prices paid for landings. Changes in revenue between any two years depends on both prices and quantities in each year, and both may be changing simultaneously. For example, an increase in the harvest of higher priced species, such as scallops can lead to an overall increase in total revenue from an LME between time periods even if quantities landed of other species decline. Although measurement of revenue change is useful, the ability to see what drives revenue change, whether it is changing harvest levels, the mix of species landed, or price changes provides additional valuable information.

Therefore, it is useful to decompose revenue change into two parts, one which is due to changing quantities (or volumes), and a second which is due to changing prices. In an LME, the quantity component will yield useful information about how the species mix of harvests are changing through time.

A Bennet indicator (BI) is used to examine revenue change between 1964 and 2015 for two major LME regions. It is composed of a volume indicator (VI), which measures changes in quantities, and a price indicator (PI) which measures changes in prices. The Bennet (1920) indicator (BI) was first used to show how a change in social welfare could be decomposed into a sum of a price and quantity change indicator (Cross and Färe 2009). It is called an indicator because it is based on differences in value between time periods, rather than ratios, which are referred to as indices. The BI is the indicator equivalent of the more popular Fisher index (Balk 2010), and has been used to examine revenue changes in Swedish pharmacies, productivity change in U.S. railroads (Lim and Lovell 2009), and dividend changes in banking operations (Grifell-Tatjé and Lovell 2004). An attractive feature of the BI is that the overall indicator is equal to the sum of its subcomponents (Balk 2010). This allows one to examine what component of overall revenue is responsible for change between time periods. This allows us to examine whether changing quantities or prices of separate species groups are driving revenue change in each EPU between 1964 and 2015.

Revenue in a given year for any species group is the product of quantity landed times price, and the sum of revenue from all groups is total revenue from the LME. In any year, both prices and quantities can change from prior years, leading to total revenue change. At time t , revenue (R) is defined as

$$R^t = \sum_{j=1}^J p_j^t y_j^t,$$

where p_j is the price for species group j , and y_j is the quantity landed of species group j . Revenue change between any two time periods, say $t+1$ and t , is then $R^{t+1} - R^t$, which can also be expressed as:

$$\Delta R = \sum_{j=1}^J p_j^{t+1} y_j^{t+1} - \sum_{j=1}^J p_j^t y_j^t.$$

This change can be decomposed further, yielding a VI and PI. The VI is calculated using the following formula (Georgianna, Lee, and Walden 2017):

$$VI = \frac{1}{2} \left(\sum_{j=1}^J p_j^{t+1} y_j^{t+1} - \sum_{j=1}^J p_j^{t+1} y_j^t + \sum_{j=1}^J p_j^t y_j^{t+1} - \sum_{j=1}^J p_j^t y_j^t \right)$$

The price indicator (PI) is calculated as follows:

$$PI = \frac{1}{2} \left(\sum_{j=1}^J y_j^{t+1} p_j^{t+1} - \sum_{j=1}^J y_j^{t+1} p_j^t + \sum_{j=1}^J y_j^t p_j^{t+1} - \sum_{j=1}^J y_j^t p_j^t \right)$$

Total revenue change between time t and $t+1$ is the sum of the VI and PI. Since revenue change is being driven by changes in the individual prices and quantities landed of each species group, changes at the species group level can be examined separately by taking advantage of the additive property of the indicator. For example, if there are five different species groups, the sum of the VI for each group will equal the overall VI, and the sum of the PI for each group will equal the overall PI.

5.1.4 Data processing

Bennet indicator time series were formatted for inclusion in the `ecodata` R package using the R code found here

5.1.5 Plotting

Code for plotting the bennet indicator can be found here.

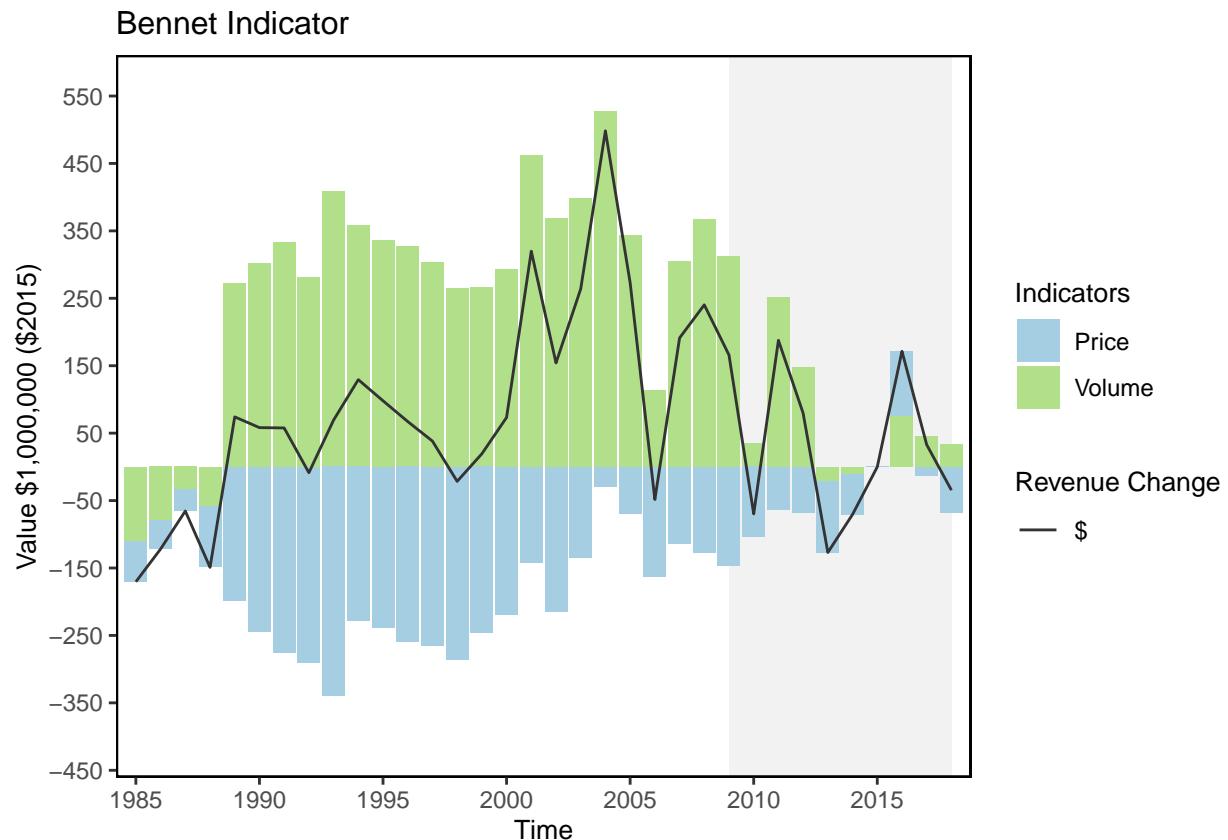


Figure 5.1: Revenue change from the long-term mean in 2015 dollars (black), Price (PI), and Volume Indicators (VI) for commercial landings in the Mid-Atlantic.

Chapter 6

Bottom temperatures

Description: Time series of annual in situ bottom temperatures on the Northeast Continental Shelf.

Indicator category: Extensive analysis; not yet published Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2019, 2020); State of the Ecosystem - Mid-Atlantic Bight (2019, 2020)

Contributor(s): Paula Fratantoni, paula.fratantoni@noaa.gov

Data steward: Kimberly Bastille, kimberly.bastille@noaa.gov

Point of contact: Paula Fratantoni, paula.fratantoni@noaa.gov

Public availability statement: Source data are publicly available at ftp://ftp.nefsc.noaa.gov/pub/hydro/matlab_files/yearly and in the World Ocean Database housed at <http://www.nodc.noaa.gov/OC5/SELECT/dbsearch.html> under institute code number 258.

6.1 Methods

6.1.1 Data sources

The bottom temperature index incorporates near-bottom temperature measurements collected on Northeast Fisheries Science Center (NEFSC) surveys between 1977-present. Early measurements were made using surface bucket samples, mechanical bathythermographs and expendable bathythermograph probes, but by 1991 the CTD – an acronym for conductivity temperature and depth – became standard equipment on all NEFSC surveys. Near-bottom refers to the deepest observation at each station that falls within 10 m of the reported water depth. Observations encompass the entire continental shelf area extending from Cape Hatteras, NC to Nova Scotia, Canada, inclusive of the Gulf of Maine and Georges Bank.

6.1.2 Data extraction

While all processed hydrographic data are archived in an Oracle database (OCDBS), we work from Matlab-formatted files stored locally.

6.1.3 Data analysis

Ocean temperature on the Northeast U.S. Shelf varies significantly on seasonal timescales. Any attempt to resolve year-to-year changes requires that this seasonal variability be quantified and removed to avoid bias. This process is complicated by the fact that NEFSC hydrographic surveys conform to a random stratified sampling design meaning that stations are not repeated at fixed locations year after year so that temperature

variability cannot be assessed at fixed station locations. Instead, we consider the variation of the average bottom temperature within four Ecological Production Units (EPUs): Middle Atlantic Bight, Georges Bank, Gulf of Maine and Scotian Shelf. Within each EPU, ocean temperature observations are extracted from the collection of measurements made within 10 m of the bottom on each survey and an area-weighted average temperature is calculated. The result of this calculation is a timeseries of regional average near-bottom temperature having a temporal resolution that matches the survey frequency in the database. Anomalies are subsequently calculated relative to a reference annual cycle, estimated using a multiple linear regression model to fit an annual harmonic (365-day period) to historical regional average temperatures from 1981-2010. The curve fitting technique to formulate the reference annual cycle follows the methodologies outlined by Mountain (1991). The reference period was chosen because it is the standard climatological period adopted by the World Meteorological Organization. The resulting anomaly time series represents the difference between the time series of regional mean temperatures and corresponding reference temperatures predicted by a reference annual cycle for the same time of year. Finally, a reference annual average temperature (calculated as the average across the reference annual cycle) is added back into the anomaly timeseries to convert temperature anomalies back to ocean bottom temperature.

6.1.4 Data processing

Derived bottom temperature data were formatted for inclusion in the `ecodata` R package using the R code found here.

6.1.5 Plotting

Code for plotting Georges Bank and Gulf of Maine bottom temperature time series can be found [here](#).

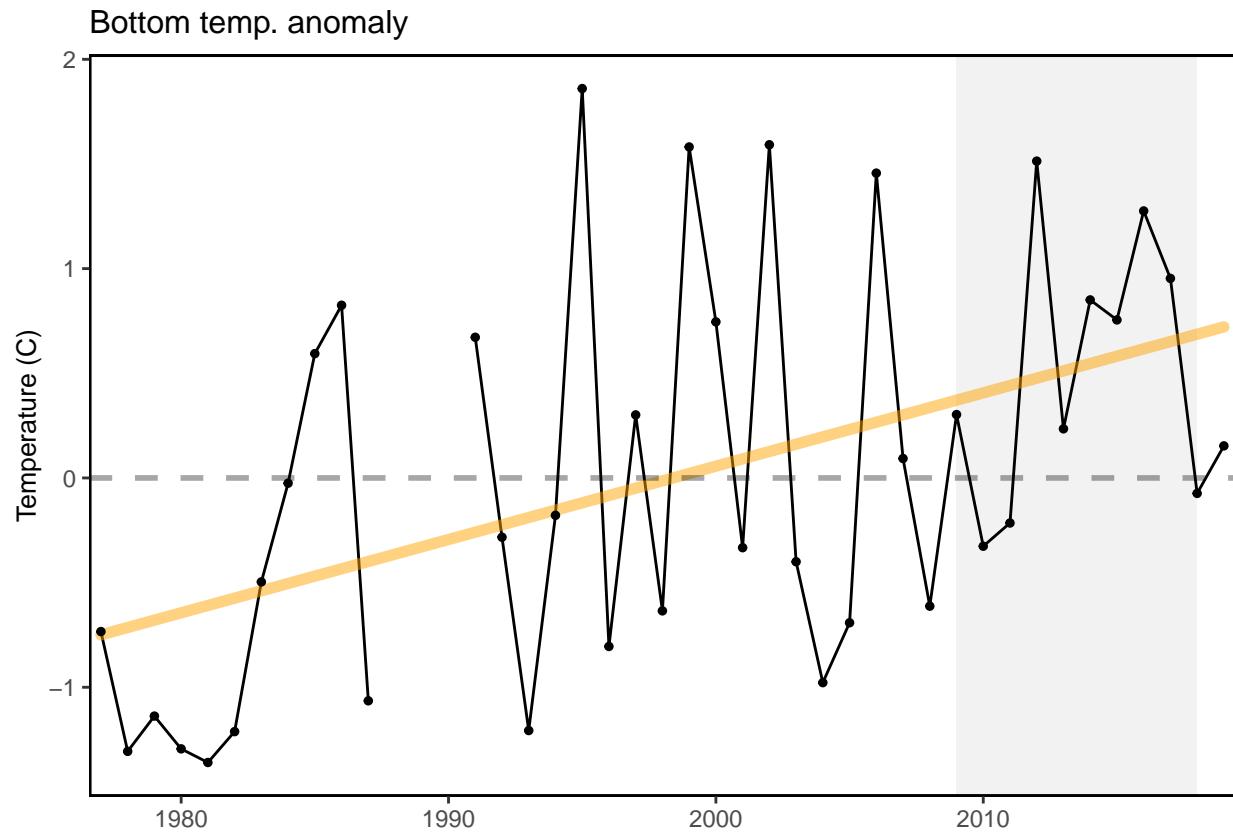


Figure 6.1: Mid-Atlantic annual bottom temperature anomalies.

Chapter 7

Catch and Fleet Diversity

Description: Permit-level species diversity and Council-level fleet diversity.

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018), State of the Ecosystem - Mid-Atlantic (2018)

Indicator category: Database pull with analysis; Published methods

Contributor(s): Geret DePiper, Min-Yang Lee

Data steward: Geret DePiper, geret.depiper@noaa.gov

Point of contact: Geret DePiper, geret.depiper@noaa.gov

Public availability statement: Source data is not publicly available due to PII restrictions. Derived time series are available for download [here](#).

7.1 Methods

Diversity estimates have been developed to understand whether specialization, or alternatively stovepiping, is occurring in fisheries of the Northeastern Large Marine Ecosystem. We use the average effective Shannon indices for species revenue at the permit level, for all permits landing any amount of NEFMC or MAFMC Fishery Management Plan (FMP) species within a year (including both Monkfish and Spiny Dogfish). We also use the effective Shannon index of fleet revenue diversity and count of active fleets to assess the extent to which the distribution of fishing changes across fleet segments.

7.1.1 Data sources

Data for these diversity estimates comes from a variety of sources, including the Commercial Fishery Dealer Database, Vessel Trip Reports, Clam logbooks, vessel characteristics from Permit database, WPU series producer price index. These data are typically not available to the public.

7.1.2 Data extraction

The following describes both the permit-level species and fleet diversity data generation. Price data was extracted from the Commercial Fishery Dealer database (CFDERS) and linked to Vessel Trip Reports by a hierarchical matching algorithm that matched date and port of landing at its highest resolution. Code used in these analyses is available upon request.

Output data was then matched to vessel characteristics from the VPS VESSEL data set. For the permit-level estimate, species groups are based off of a slightly refined NESPP3 code (Table 7.1), defined in the data as “myspp”, which is further developed in the script to rectify inconsistencies in the data.

Table 7.1: Species grouping

Group	NESPP3	Common Name	Scientific Name
	470	ALBACORE	THUNNUS ALALUNGA
	494	ATLANTIC SHARPNOSE SHARK	RHIZOPRIONODON TERRAEVVAE
	354	BIGEYE THRESHER SHARK	ALOPIAS SUPERCILIOSUS
	469	BIGEYE TUNA	THUNNUS OBESUS
	487	BLACKTIP SHARK	CARCHARHINUS LIMBATUM
	493	BLUE SHARK	PRIONACE GLAUCA
	467	BLUEFIN TUNA	THUNNUS THYNNUS
	468	LITTLE TUNNY	EUTHYNNUS ALLETTERATUS
	358	LONGFIN MAKO	ISURUS PAUCUS
	481	PORBEAGLE SHARK	LAMNA NASUS
	349	SAND TIGER	CARCHARIAS TAURUS
	482	SANDBAR SHARK	CARCHARHINUS PLUMBEUS
Highly Migratory Species	359	SHARK,UNC	CHONDRICHTHYES
	355	SHORTFIN MAKO	ISURUS OXYRINCHUS
	466	SKIPJACK TUNA	KATSUWONUS PELAMIS
	432	SWORDFISH	XIPIAS GLADIUS
	353	THRESHER SHARK	ALOPIAS VULPINUS
	491	TIGER SHARK	GALEOCERDO CUVIER
	471	YELLOWFIN TUNA	THUNNUS ALBACARES
Monkfish in Mid-Atlantic Waters	11	GOOSEFISH	LOPHIUS AMERICANUS
	12	GOOSEFISH	LOPHIUS AMERICANUS
Atlantic Scallops	800	SEA SCALLOP	PLACOPECTEN MAGELLANICUS
	737	MANTIS SHRIMP UNCL	STOMATOPODA
	737	MANTIS SHRIMPS	STOMATOPODA
	736	NORTHERN SHRIMP	PANDALUS BOREALIS
Shrimp	738	SHRIMP,ATLANTIC & GULF,BROWN	PANAEIDAE
	735	SHRIMP,UNC (CARIDEA)	CARIDEA
	368	BARNDOR SKATE	DIPTURUS LAEVIS
	372	CLEARNOSE SKATE	RAJA EGLANERIA
	366	LITTLE SKATE	LEUCORAJA ERINACEA
	365	OCELLATE SKATES	RAJA
	365	SKATES	RAJIDAE
	373	SKATES,LITTLE/WINTER MIXED	LEUCORAJA

Table 7.1: Species grouping (*continued*)

Group	NESPP3	Common Name	Scientific Name
Skates			
	369	SMOOTH SKATE	MALACORAJA SENTA
	370	THORNY SKATE	AMBLYRAJA RADIATA
	367	WINTER SKATE	LEUCORAJA OCELLATA
Herring	168	ATLANTIC HERRING	CLUPEA HARENGUS
Ocean Quahog	754	OCEAN QUAHOG	ARCTICA ISLANDICA
Surf Clam	769	ATLANTIC SURFCLAM	SPISULA SOLIDISSIMA
	444	BLUELINE TILEFISH	CAULOLATILUS MICROPS
	445	SAND TILEFISH	MALACANTHUS PLUMIERI
Tilefish	446	TILEFISH	LOPHOLATILUS CHAMELEONTICEPS
	447	TILEFISH,UNC	MALACANTHIDAE
	335	BLACK SEA BASS	CENTROPRISTIS STRIATA
Fluke & Black Seabass	121	SUMMER FLOUNDER	PARALICHTHYS DENTATUS
	51	BUTTERFISH	PEPRILUS TRIACANTHUS
Butterfish & Hake	152	RED HAKE	UROPHYCIS CHUSS
	509	SILVER HAKE	MERLUCCIUS BILINEARIS
Bluefish in Mid-Atlantic Waters	23	BLUEFISH	POMATOMUS SALTATRIX
Spiny Dogfish	352	SPINY DOGFISH	SQUALUS ACANTHIAS
Northern Shortfin Squid	802	NORTHERN SHORTFIN SQUID	ILLEX ILLECEBROSUS
American Lobster	727	AMERICAN LOBSTER	HOMARUS AMERICANUS
Longfin Squid	801	LONGFIN SQUID	LOLIGO PEALEII
Menhaden	221	MENHADEN	BREVOORTIA
Offshore Hake	508	OFFSHORE HAKE	MERLUCCIUS ALBIDUS
Scup in Mid-Atlantic Waters	329	SCUP	STENOTOMUS CHRYSOPS
Windowpane Flounder in New England Waters	125	WINDOWPANE	SCOPHTHALMUS AQUOSUS
Ocean Pout in New England Waters	250	OCEAN POUT	ZOARCES AMERICANUS
Wolfish	512	ATLANTIC WOLFFISH	ANARHICHAS LUPUS
Winter Flounder in Mid-Atlantic Waters	120	WINTER FLOUNDER	PSEUDOPLEURONECTES AMERICANUS
Yellowtail Flounder in Mid-Atlantic Waters	123	YELLOWTAIL FLOUNDER	LIMANDA FERRUGINEA
Unclassified Hake	155	Unclassified Hake	
White Hake in Mid-Atlantic Waters	153	WHITE HAKE	UROPHYCIS TENUIS
	23	BLUEFISH	POMATOMUS SALTATRIX

Table 7.1: Species grouping (*continued*)

Group	NESPP3	Common Name	Scientific Name
Bluefish & Scup in New England Waters	329	SCUP	STENOTOMUS CHRYSOPOS
Halibut in New England Waters	159	ATLANTIC HALIBUT	HIPPOGLOSSUS HIPPOGLOSSUS
	240	ACADIAN REDFISH	SEBASTES FASCIATUS
	124	AMERICAN PLAICE	HIPPOGLOSSOIDES PLATESSOIDES
	81	ATLANTIC COD	GADUS MORHUA
	11	GOOSEFISH	LOPHIUS AMERICANUS
	12	GOOSEFISH	LOPHIUS AMERICANUS
	147	HADDOCK	MELANOGRAMMUS AEGLEFINUS
Groundfish in New England Waters	269	POLLOCK	POLLACHIUS VIRENS
	153	WHITE HAKE	UROPHYCIS TENUIS
	120	WINTER FLOUNDER	PSEUDOPLEURONECTES AMERICANUS
	122	WITCH FLOUNDER	GLYPTOCEPHALUS CYNOGLOSSUS
	123	YELLOWTAIL FLOUNDER	LIMANDA FERRUGINEA
	240	ACADIAN REDFISH	SEBASTES FASCIATUS
	124	AMERICAN PLAICE	HIPPOGLOSSOIDES PLATESSOIDES
	81	ATLANTIC COD	GADUS MORHUA
	159	ATLANTIC HALIBUT	HIPPOGLOSSUS HIPPOGLOSSUS
	512	ATLANTIC WOLFFISH	ANARHICHAS LUPUS
	147	HADDOCK	MELANOGRAMMUS AEGLEFINUS
Groundfish in Mid-Atlantic Waters	269	POLLOCK	POLLACHIUS VIRENS
	122	WITCH FLOUNDER	GLYPTOCEPHALUS CYNOGLOSSUS
	155	Unclassified Hake	
	250	OCEAN POUT	ZOARCES AMERICANUS
Windowpane Flounder & Ocean Pout in Mid-Atlantic Waters	125	WINDOWPANE	SCOPHTHALMUS AQUOSUS

For the fleet diversity metric, gears include scallop dredge (gearcodes DRS, DSC, DTC, and DTS), other dredges (gearcodes DRM, DRO, and DRU), gillnet (gearcodes GND, GNT, GNO, GNR, and GNS), hand (gearcode HND), longline (gearcodes LLB and LLP), bottom trawl (gearcodes OTB, OTF, OTO, OTC, OTS, OHS, OTR, OTT, and PTB), midwater trawls (gearcode OTM and PTM), pot (gearcodes PTL, PTW, PTC, PTE, PTF, PTH, PTL, PTO, PTS, and PTX), purse seine (gearcode PUR), and hydraulic clam dredge (gearcode DRC). Vessels were further grouped by length categories of less than 30 feet, 30 to 50 feet, 50 to 75 feet, and 75 feet and above. All revenue was deflated to real dollars using the “WPU0223” Producer Price Index with a base of January 2015. Stata code for data processing is available [here](#).

7.1.3 Data analysis

This permit-level species effective Shannon index is calculated as

$$\exp\left(-\sum_{i=1}^N p_{ijt} \ln(p_{ijt})\right)$$

for all j , with p_{ijt} representing the proportion of revenue generated by species or species group i for permit j in year t , and is a composite of richness (the number of species landed) and abundance (the revenue generated from each species). The annual arithmetic mean value of the effective Shannon index across permits is used as the indicator of permit-level species diversity.

In a similar manner, the fleet diversity metric is estimated as

$$\exp\left(-\sum_{i=1}^N p_{kt} \ln(p_{kt})\right)$$

for all k , where p_{kt} represents the proportion of total revenue generated by fleet segment k (gear and length combination) per year t . The indices each run from 1996 to 2017. A count of the number of fleets active in every year is also provided to assess whether changes in fleet diversity are caused by shifts in abundance (number of fleets), or evenness (concentration of revenue). The work is based off of analysis conducted in Thunberg and Correia (2015) and published in Gaichas et al. (2016).

7.1.4 Data processing

Catch and fleet diversity indicators were formatted for inclusion in the `ecodata` R package using the R script found [here](#).

7.1.5 Plotting

Code for plotting the catch and fleet diversity indicator can be found [here](#).

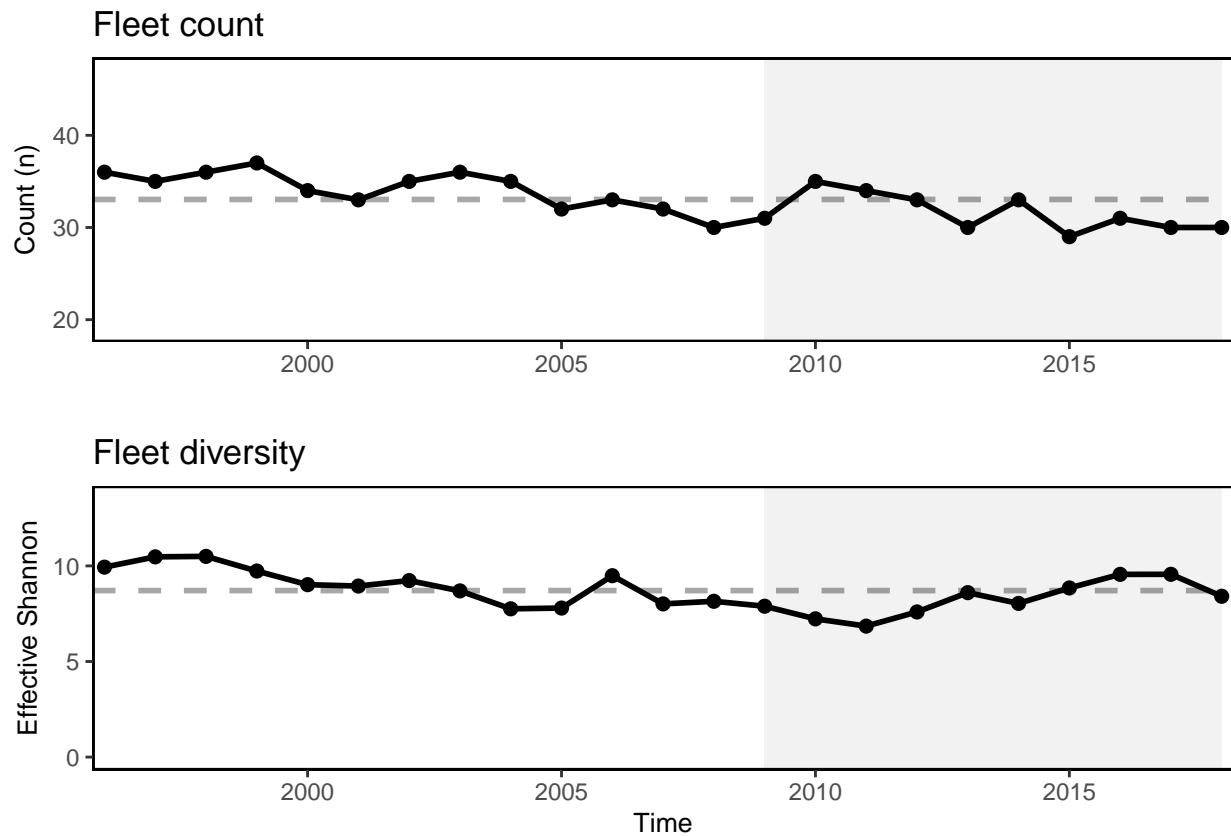


Figure 7.1: Fleet diversity and fleet count in the Mid-Atlantic.

Chapter 8

Chesapeake Bay Salinity

Description: Chesapeake Bay Salinity

Found in: State of the Ecosystem - Mid-Atlantic (2020)

Indicator category: Database pull with analysis

Contributor(s): Bruce Vogt, Charles Pellerin

Data steward: Charles Pellerin, charles.pellerin@noaa.gov

Point of contact: Bruce Vogt, bruce.vogt@noaa.gov

Public availability statement: Source data are publicly available.

8.1 Methods

8.1.1 Data sources

Low salinity levels recorded by NOAA Chesapeake Bay Office's Chesapeake Bay Interpretive Buoy System (CBIBS).

NOAA Chesapeake Bay Office <https://buoybay.noaa.gov/node/160> Chesapeake Bay Program https://www.chesapeakebay.net/news/blog/what_this_summers_rainfall_could_mean_for_the_bay Maryland Department of Natural Resources (Jodi Baxter, Lynn Fegley) Virginia Marine Resources Commission (Andrew Button) University of Maryland Center for Environmental Science, Horn Point Laboratory Oyster Hatchery (Stephanie Tobash Alexander)

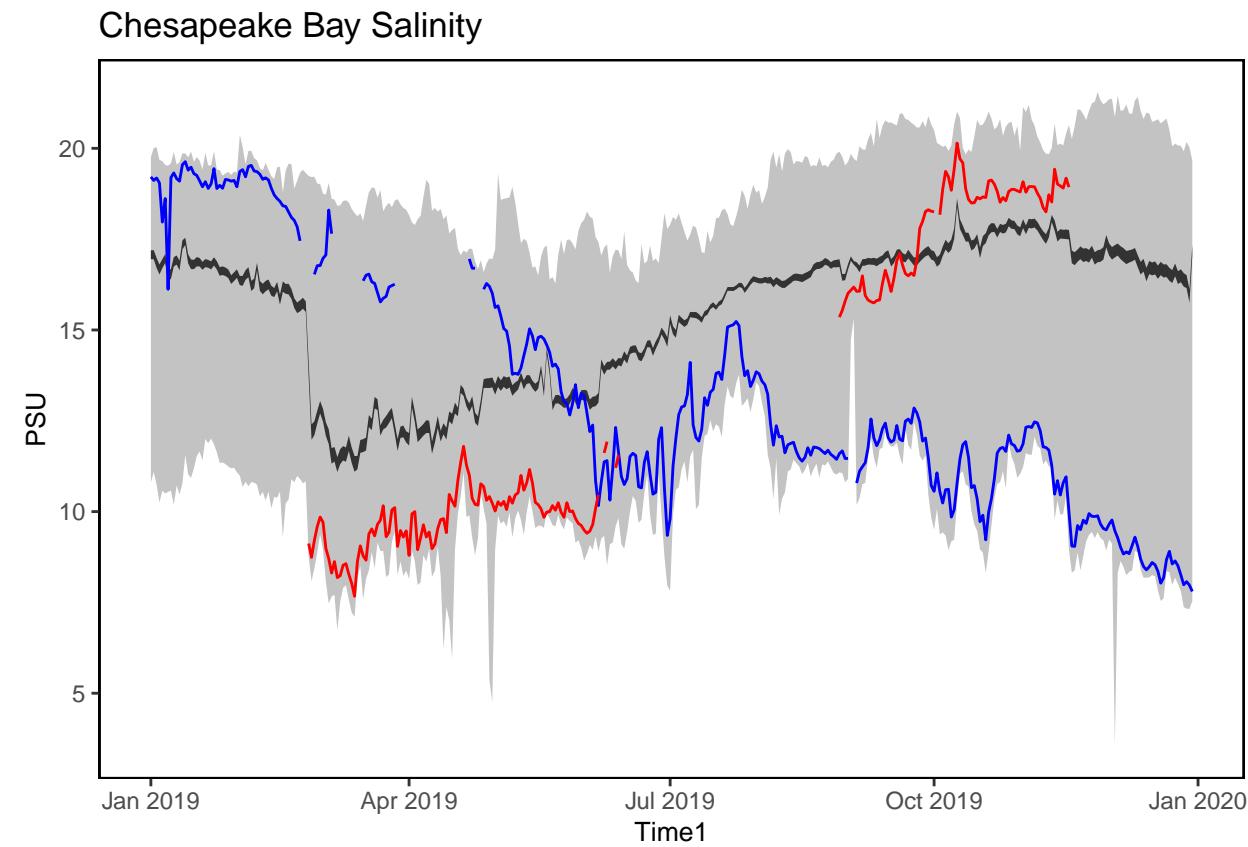
8.1.2 Data extraction

8.1.3 Data analysis

8.1.4 Data processing

Code for processing salinity data can be found [here](#).

8.1.5 Plotting



Chapter 9

Chesapeake Bay Water Quality Standards Attainment

Description: A multimetric indicator describing the attainment status of Chesapeake Bay with respect to three water quality standards criteria, namely, dissolved oxygen, chlorophyll-a, and water clarity/submerged aquatic vegetation.

Indicator category: Published method; Database pull with analysis

Found in: State of the Ecosystem - Mid-Atlantic (2019)

Contributor(s): Qian Zhang, Rebecca Murphy, Richard Tian, Melinda Forsyth, Emily Trentacoste, Jeni Keisman, and Peter Tango.

Data steward: Qian Zhang, qzhang@chesapeakebay.net

Point of contact: Qian Zhang, qzhang@chesapeakebay.net

Public availability statement: Data are publicly available (see Data Sources below).

9.1 Methods

To protect the aquatic living resources of Chesapeake Bay, the Chesapeake Bay Program (CBP) partnership has developed a guidance framework of ambient water quality criteria with designated uses and assessment procedures for dissolved oxygen, chlorophyll-a, and water clarity/submerged aquatic vegetation (SAV) (USEPA 2003). To achieve consistent assessment over time and between jurisdictions, a multimetric indicator was proposed by the CBP partnership to provide a means for tracking the progress in all 92 management segments of Chesapeake Bay (USEPA 2017). This indicator has been computed for each three-year assessment period since 1985-1987, providing an integrated measure of Chesapeake Bay's water quality condition over the last three decades.

9.1.1 Data sources

The multimetric indicator required monitoring data on dissolved oxygen (DO) concentrations, chlorophyll-a concentrations, water clarity, SAV acreage, water temperature, and salinity. SAV acreage has been measured by the Virginia Institute of Marine Science in collaboration with the CBP, which is available via <http://web.vims.edu/bio/sav/StateSegmentAreaTable.htm>. Data for all other parameters were obtained from the CBP Water Quality Database. These data have been routinely reported to the CBP by the Maryland

Department of Natural Resources, Virginia Department of Environmental Quality, Old Dominion University, Virginia Institute of Marine Science, and citizen/volunteer monitoring initiatives.

9.1.2 Data analysis

Criteria attainment assessment

Monitoring data of DO, chlorophyll-a, and water clarity/SAV were processed and compared with water quality criteria thresholds according to different designated uses (DUs). These DUs are migratory spawning and nursery (MSN), open water (OW), deep water (DW), deep channel (DC), and shallow water (SW), which reflect the seasonal nature of water column structure and the life history needs of living resources. Station-level DO and chlorophyll-a data were spatially interpolated in three dimensions.

Salinity and water temperature data were used to compute the vertical density structure of the water column, which was translated into layers of different DUs. Criteria attainment was determined by comparing violation rates over a 3-year period to a reference cumulative frequency distribution that represents the extent of allowable violation. This approach was implemented using FORTRAN codes, which are provided as a zipped folder. For water clarity/SAV, the single best year in the 3-year assessment period was compared with the segment-specific acreage goal, the water clarity goal, or a combination of both. For more details, refer to the Methods section of Zhang et al. (2018).

Indicator calculation

The multimetric indicator quantifies the fraction of segment-DU-criterion combinations that meet all applicable season-specific thresholds for each 3-year assessment period from 1985-1987 to 2015-2017. For each 3-year assessment period, all applicable segment-DU-criterion combinations were evaluated in a binomial fashion and scored 1 for “in attainment” and 0 for “nonattainment”. The classified status of each segment-DU-criterion combination was weighted via segments’ surface area and summed to obtain the multimetric index score. This weighting scheme was adopted for two reasons: (1) segments vary in size over four orders of magnitude, and (2) surface area of each segment does not change with time or DUs, unlike seasonally variable habitat volume or bottom water area (USEPA 2017). For more details, refer to the Methods section of Zhang et al. (2018).

The indicator provides an integrated measure of Chesapeake Bay’s water quality condition (Figure 1). In 2015-2017, 42% of all tidal water segment-DU-criterion combinations are estimated to have met or exceeded applicable water quality criteria thresholds, which marks the best 3-year status since 1985-1987. The indicator has a positive and statistically significant trend from 1985 to 2017, which shows that Chesapeake Bay is on a positive trajectory toward recovery. This pattern was statistically linked to total nitrogen reduction, indicating responsiveness of attainment status to management actions implemented to reduce nutrients in the system.

Patterns of attainment of individual DUs are variable (Figure 2). Changes in OW-DO, DC-DO, and water clarity/SAV have shown long-term improvements, which have contributed to overall attainment indicator improvement. By contrast, the MSN-DO attainment experienced a sharp spike in the first few assessment periods but generally degraded after the 1997-1999, which has implications to the survival, growth, and reproduction of the migratory and resident tidal freshwater fish during spawning and nursery season in the tidal freshwater to low-salinity habitats. The status and trends of tidal segments’ attainment may be used to inform siting decisions of aquaculture operations in Chesapeake Bay.

9.1.3 Data processing

The indicator data set was formatted for inclusion in the ecodata R package using the R script found here.

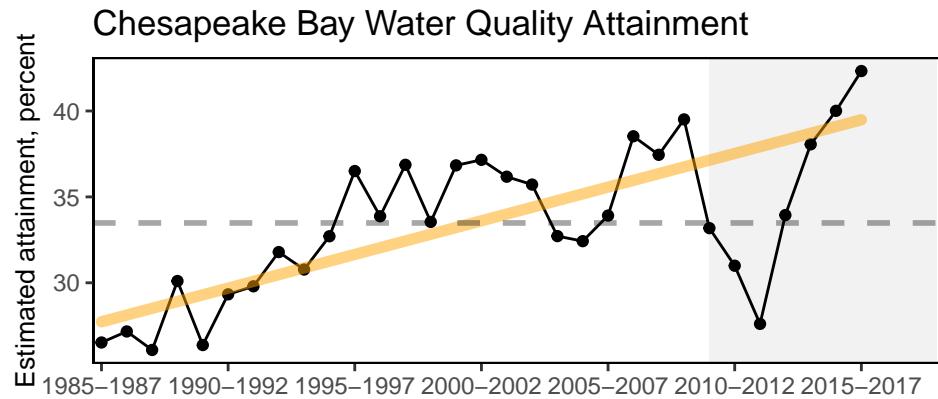


Figure 9.1: Time series of the multimetric indicator score for estimated Chesapeake Bay water quality standards attainment for each 3-year assessment period between 1985-1987 and 2015-2017. A significant positive trend for the time series is shown by the orange line ($p < 0.05$).

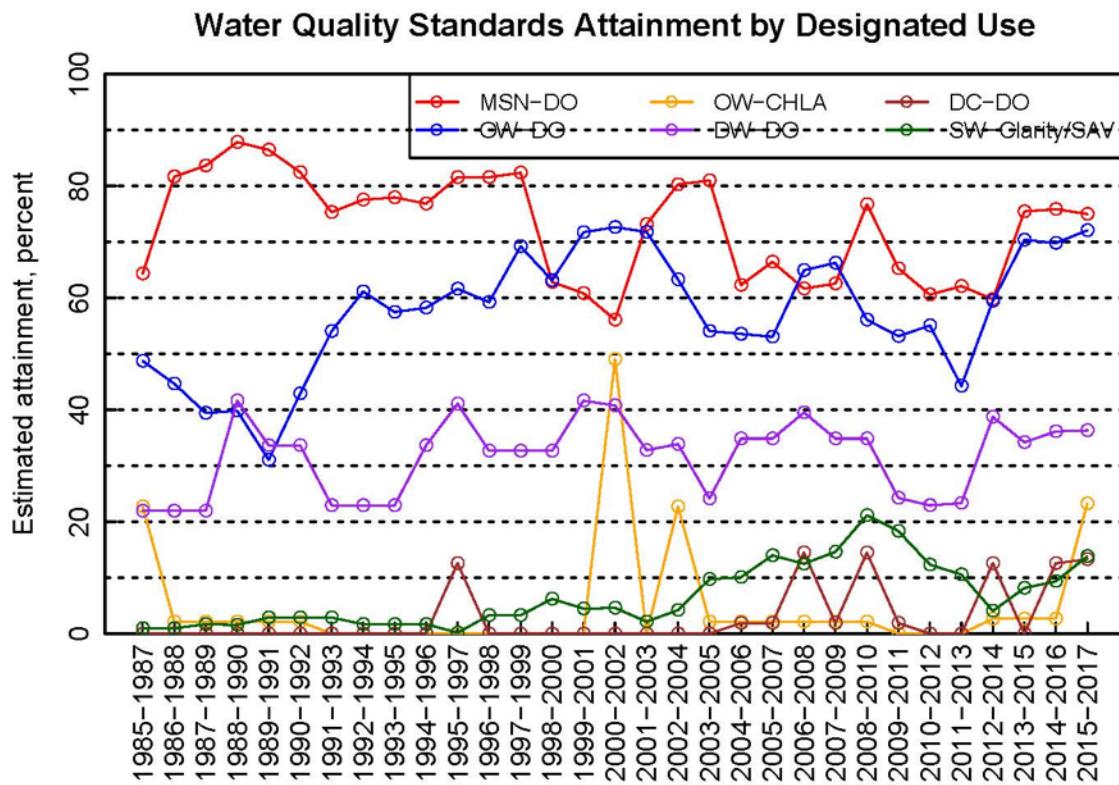


Figure 9.2: Time series of the estimated attainment of water quality standards (i.e., DO: dissolved oxygen; CHLA: chlorophyll-a; Clarity/SAV: water clarity/submerged aquatic vegetation) for five Chesapeake Bay designated uses (MSN: migratory spawning and nursery; OW: open water; DW: deep water; DC: deep channel; SW: shallow water) for each 3-year assessment period between 1985-1987 and 2015-2017.

Chapter 10

Chlorophyll *a* and Primary Production

Description: Chlorophyll *a* and Primary Production

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018, 2019, 2020), State of the Ecosystem - Mid-Atlantic (2018, 2019, 2020)

Indicator category: Database pull; Database pull with analysis; Published methods

Contributor(s): Kimberly Hyde

Data steward: Kimberly Hyde, kimberly.hyde@noaa.gov

Point of contact: Kimberly Hyde, kimberly.hyde@noaa.gov

Public availability statement: Source data used in these analyses will be made publicly available. Derived data used in State of the Ecosystem Reports can be found here.

10.1 Methods

10.1.1 Data sources

Level 1A ocean color remote sensing data from the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) (NASA Ocean Biology Processing Group 2018) on the OrbView-2 satellite and the Moderate Resolution Imaging Spectroradiometer (MODIS) (NASA Ocean Biology Processing Group 2017) on the Aqua satellite were acquired from the NASA Ocean Biology Processing Group (OBPG). Sea Surface Temperature (SST) data included the 4 km nighttime NOAA Advanced Very High Resolution Radiometer (AVHRR) Pathfinder (Casey et al. 2010; Saha et al. 2018) and the Group for High Resolution Sea Surface Temperature (GHRSST) Multiscale Ultrahigh Resolution (MUR, version 4.1) Level 4 (Chin, Vazquez-Cuervo, and Armstrong 2017; Project 2015) data.

10.1.2 Data extraction

NA

10.1.3 Data analysis

The SeaWiFS and MODIS L1A files were processed using the NASA Ocean Biology Processing Group SeaDAS software version 7.4. All MODIS files were spatially subset to the U.S. East Coast (SW longitude=-82.5, SW latitude=22.5, NE longitude=-51.5, NE latitude=48.5) using L1AEXTRACT_MODIS. SeaWiFS files were subset using the same coordinates prior to begin downloaded from the Ocean Color Web Browser. SeaDAS's L2GEN program was used to generate Level 2 (L2) files using the default settings and optimal ancillary files, and the L2BIN program spatially and temporally aggregated the L2 files to create daily Level 3 binned (L3B) files. The daily files were binned at 2 km resolution that are stored in a global, nearly equal-area, integerized sinusoidal grids and use the default L2 ocean color flag masks. The global SST data were also subset to the same East Coast region and remapped to the same sinusoidal grid.

The L2 files contain several ocean color products including the default chlorophyll *a*; product (CHL-OCI), photosynthetic available radiation (PAR), remote sensing reflectance ($R_{rs}(\lambda)$), and several inherent optical property products (IOPs). The CHL-OCI product combines two algorithms, the O'Reilly band ratio (OCx) algorithm (O'Reilly et al. 1998) and the Hu color index (CI) algorithm (Hu, Lee, and Franz 2012). The SeaDAS default CHL-OCI algorithm diverges slightly from Hu, Lee, and Franz (2012) in that the transition between CI and OCx occurs at $0.15 < \text{CI} < 0.2 \text{ mg m}^{-3}$ to ensure a smooth transition. The regional chlorophyll *a* algorithm by Pan et al. (2008) was used to create a second chlorophyll product (CHL-PAN). CHL-PAN is an empirical algorithm derived from *in situ* sampling within the Northeast Large Marine Ecosystem (NE-LME) and demonstrated significant improvements from the standard NASA operational algorithm in the NES-LME (Pan et al. 2010). A 3rd-order polynomial function (Equation (10.1)) is used to derive [CHL-PAN] from Rrs band ratios (RBR):

$$\log[\text{CHL-PAN}] = A_0 + A_1X + A_2X^2 + A_3X^3, \quad (10.1)$$

where $X = \log(R_{rs}(\lambda_1)/R_{rs}(\lambda_2))$ and $A_i(i = 0, 1, 2, \text{ or } 3)$ are sensor and RBR specific coefficients:

- If SeaWiFS and RBR is $R_{rs}(490)/R_{rs}(555)(R_{3/5})$ then: $A_0 = 0.02534, A_1 = -3.033, A_2 = 2.096, A_3 = -1.607$
- If SeaWiFS and RBR is $R_{rs}(490)/R_{rs}(670)(R_{3/6})$ then: $A_0 = 1.351, A_1 = -2.427, A_2 = 0.9395, A_3 = -0.2432$
- If MODIS and RBR is $R_{rs}(488)/R_{rs}(547)(R_{3/5})$ then: $A_0 = 0.03664, A_1 = -3.451, A_2 = 2.276, A_3 = -1.096$
- If MODIS and RBR is $R_{rs}(488)/R_{rs}(667)(R_{3/6})$ then: $A_0 = 1.351, A_1 = -2.427, A_2 = 0.9395, A_3 = -0.2432$

$C_{3/5}$ and $C_{3/6}$ were calculated for each sensor specific RBR ($R_{3/5}$ and $R_{3/6}$ respectively) and then the following criteria were used to determine to derive CHL-PAN:

If $R_{3/5} > 0.15$ or $R_6 < 0.0001$ then $\text{CHL-PAN} = C_{3/5}$;

Otherwise, $\text{CHL-PAN} = \max(C_{3/5}, C_{3/6})$,

where R_6 is $R_{rs}(670)$ (SeaWiFS) or $R_{rs}(667)$ (Pan et al. 2010).

The Vertically Generalized Production Model (VGPM) estimates net primary production (PP) as a function of chlorophyll *a*, photosynthetically available light and the photosynthetic efficiency (Behrenfeld and Falkowski 1997). In the VGPM-Eppley version, the original temperature-dependent function to estimate the chlorophyll-specific photosynthetic efficiency is replaced with the exponential "Eppley" function (equation PP1) as modified by Morel (1991). The VGPM calculates the daily amount of carbon fixed based on the maximum rate of chlorophyll-specific carbon fixation in the water column, sea surface daily photosynthetically available radiation, the euphotic depth (the depth where light is 1% of that at the surface), chlorophyll *a* concentration, and the number of daylight hours (Equation (10.2)).

$$P_{max}^b(SST) = 4.6 * 1.065^{SST-20^0} \quad (10.2)$$

Where P_{max}^b is the maximum carbon fixation rate and SST is sea surface temperature.

$$PP_{eu} = 0.66125 * P_{max}^b * \frac{I_0}{I_0 + 4.1} * Z_{eu} * CHL * DL \quad (10.3)$$

Where PP_{eu} is the daily amount of carbon fixed integrated from the surface to the euphotic depth ($\text{mgC m}^{-2} \text{ day}^{-1}$), P_{max}^b is the maximum carbon fixation rate within the water column ($\text{mgC mgChl}^{-1} \text{ hr}^{-1}$), I_0 is the daily integrated molar photon flux of sea surface PAR (mol quanta $\text{m}^{-2} \text{ day}^{-1}$), Z_{eu} is the euphotic depth (m), CHL is the daily interpolated CHL-OCl (mg m^{-3}), and DL is the photoperiod (hours) calculated for the day of the year and latitude according to Kirk (1994). The light dependent function ($I_0/(I_0 + 4.1)$) describes the relative change in the light saturation fraction of the euphotic zone as a function of surface PAR (I_0). Z_{eu} is derived from an estimate of the total chlorophyll concentration within the euphotic layer (CHL_{eu}) based on the Case I models of Morel and Berthon (1989):

- For $CHL_{eu} > 10.0$ $Z_{eu} = 568.2 * CHL_{eu}^{-0.746}$
- For $CHL_{eu} \leq 10.0$ $Z_{eu} = 200.0 * CHL_{eu}^{-0.293}$
- For $CHL_0 \leq 1.0$ $CHL_{eu} = 38.0 * CHL_0^{0.425}$
- For $CHL_0 > 1.0$ $CHL_{eu} = 40.2 * CHL_0^{0.507}$

Where CHL_0 is the surface chlorophyll concentration.

Prior to being input into the VGPM-Eppley model, the daily CHL-OCl and AVHRR SST data were temporally interpolated and smoothed (CHL-OCl_{INT} and SST_{INT} respectively) to increase the data coverage and better match data collected from different sensors and different times. The daily PAR data are not affected by cloud cover and MUR SST data is a blended/gap free data product so these products were not interpolated.

Daily data at each pixel location covering the entire date range were extracted to create a pixel time series ($D_{x,y}$). ($D_{x,y}$) are linearly interpolated based on days in the time series using interp.x.pro. Prior to interpolation, the CHL data are log-transformed to account for the log-normal distribution of chlorophyll data (Campbell 1995). Interpolating the entire times series requires a large amount of processing time so the series was processed one year at a time. Each yearly series included 60 days from the previous year and 60 days from the following year to improve the interpolation at the beginning and end of the year. Following interpolation, the data are smoothed with a tri-cube filter (width=7) using IDL's CONVOL program. In order to avoid over interpolating data when there were several days of missing data in the time series, the interpolated data were removed and replaced with blank data if the window of interpolation spanned more than 7 days for CHL or 10 days for SST. After all $D_{x,y}$ pixels had been processed, the one-dimensional pixel time series were converted back to two-dimensional daily files.

Statistics, including the arithmetic mean, geometric mean (for CHL and PP), standard deviation, and coefficient of variation were calculated at daily (3 and 8-day running means), weekly, monthly, and annual time steps and for several climatological periods. Annual statistics used the monthly means as inputs to avoid a summer time bias when more data is available due to reduced cloud cover. The daily, weekly, monthly and annual climatological statistics include the entire time series for each specified period. For example, the climatological January uses the monthly mean from each January in the time series and the climatological annual uses the annual mean from each year. The CHL and PP climatological statistics include data from both SeaWiFS (1997-2007) and MODIS (2008-2017).

Weekly, monthly and annual anomalies were calculated for each product by taking the difference between the mean of the input time period (i.e. week, month, year) and the climatological mean for the same period. Because bio-optical data are typically log-normally distributed (Campbell 1995), the CHL and PP data were first log-transformed prior to taking the difference and then untransformed, resulting in an anomaly ratio.

The ecological production unit (EPU) shapefile that excludes the estuaries was used to spatially extract all data location within an ecoregion from the statistic and anomaly files. The median values, which are equivalent to the geometric mean, were used for the CHL and PP data. For the extended time series, the 1998-2007 data use the SeaWiFS ocean color products and MODIS-Aqua products were used from 2008 to 2017. Prior to June 2002, AVHRR Pathfinder data are used as the SST source and MUR SST in subsequent years.

10.1.4 Data processing

CHL and PPD time series were formatted for inclusion in the `ecodata` R package using the R code found here.

10.1.5 Plotting

Chl *a* and primary production data were also examined in relation to the long-term means of each series. The figures below show data specific to the Mid-Atlantic Bight. The code for the plots can be found [here](#).

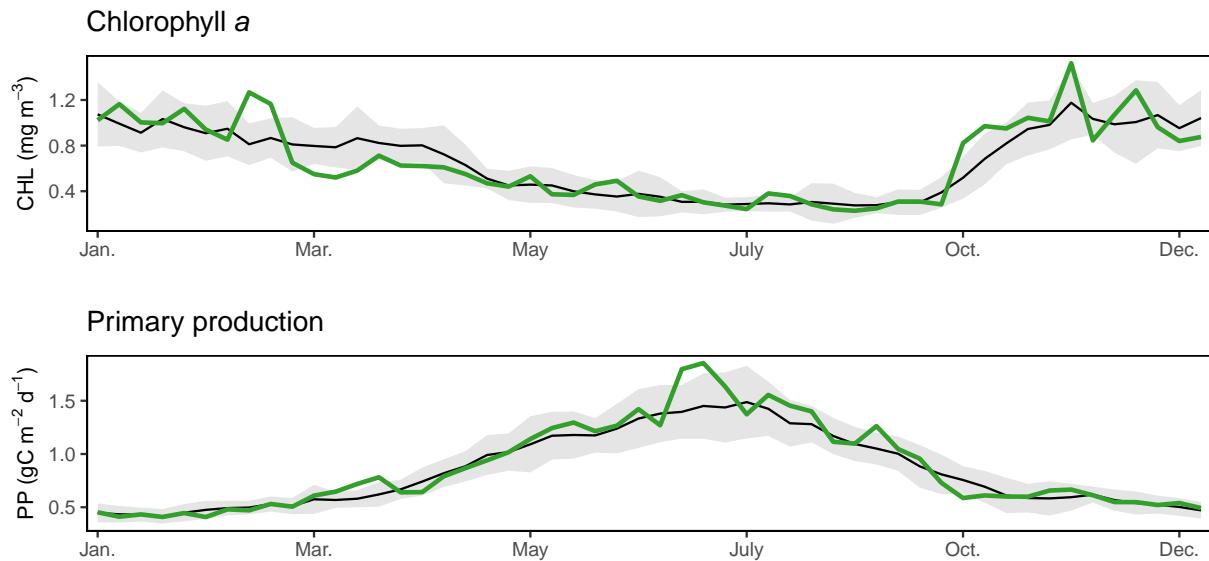


Figure 10.1: Weekly chlorophyll concentrations in the Mid-Atlantic are shown by the colored line for 2019. The long-term mean is shown in black, and shading indicates +/- 1 sample SD.

In the figure below, we show monthly primary productivity on an annual time step in the Mid-Atlantic Bight. The code for this can be found [here](#)

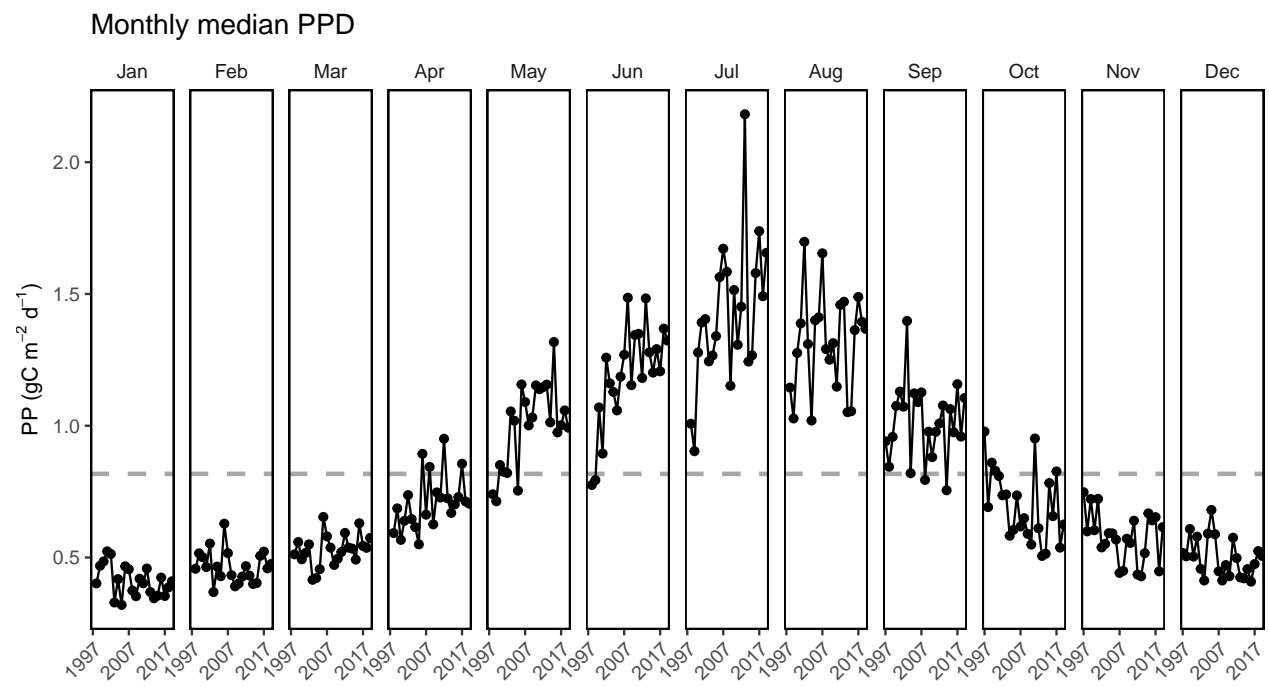


Figure 10.2: Monthly primary production trends show the annual cycle (i.e. the peak during the summer months) and the changes over time for each month.

Chapter 11

Cold Pool Index

Description: Cold Pool Index

Found in: State of the Ecosystem - Mid-Atlantic (2020)

Indicator category: Published methods

Contributor(s): Chris Melrose

Data steward: Kimberly Bastille

Point of contact: Chris Melrose chris.melrose@noaa.gov

Public availability statement: Source data are publicly available.

11.1 Methods

11.1.1 Data sources

NEFSC Hydrographic Database This data represents the annual mean bottom temperature residual for Sept-Oct in the Mid-Atlantic Bight cold pool region from 1977-2018.

11.1.2 Data extraction

11.1.3 Data analysis

Methods published T. Miller, Hare, and Alade (2016), original MATLAB source code used in that paper was provided by Jon Hare and used in this analysis.

11.1.4 Data processing

Code used to process the cold pool indicator can be found in the `ecodata` package here.

11.1.5 Plotting

The plot below was built using the code found here.

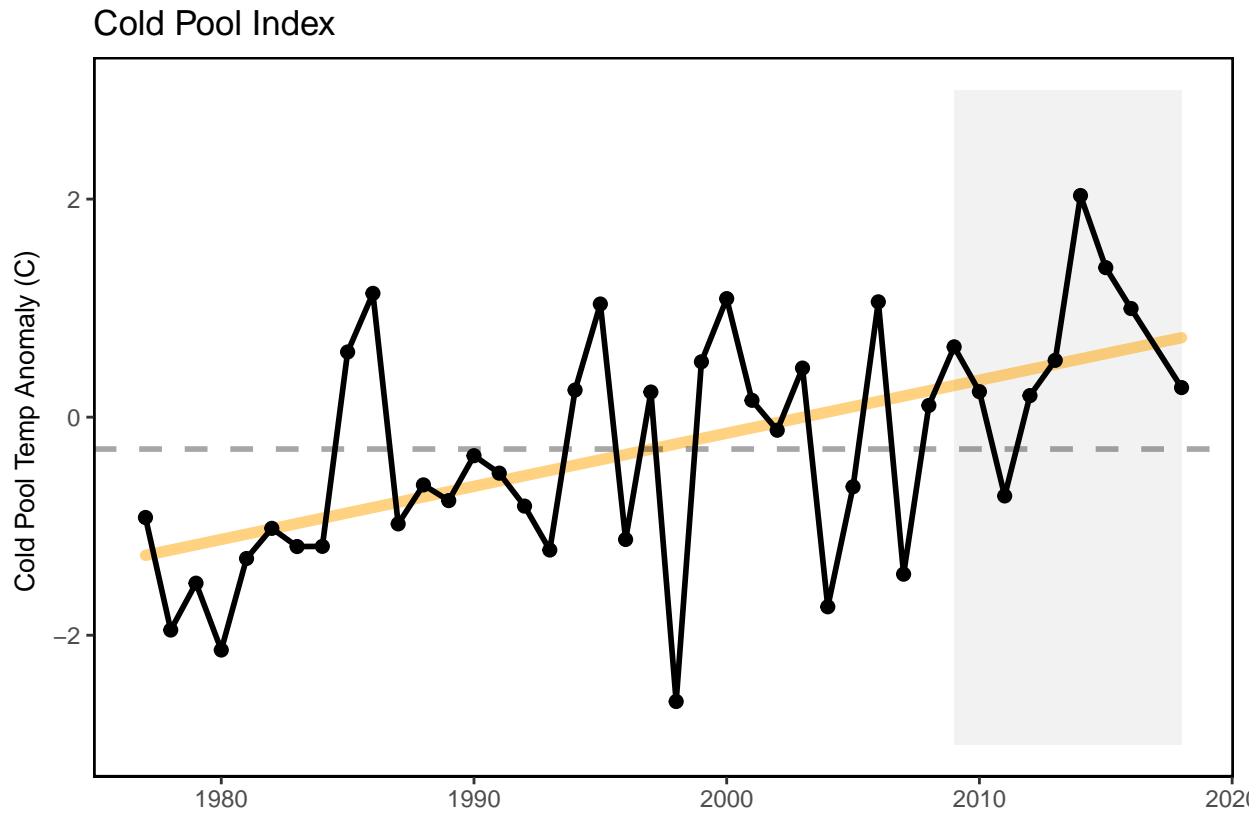


Figure 11.1: Cold Pool Index

Chapter 12

Community Engagement

Description: Fishing community engagement

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2020), State of the Ecosystem - Mid-Atlantic (2020)

Indicator category: Database pull with analysis

Contributor(s): Lisa L. Colburn

Data steward: Lisa L. Colburn

Point of contact: Lisa L. Colburn

Public availability statement: The source data used to construct the commercial fishing engagement and reliance indices include confidential information and are not available publicly. However, the commercial fishing engagement and reliance indices are not confidential so are available to the public. All calculated indices can be found [here](#).

12.1 Methods

12.1.1 Data sources

NOAA Fisheries' Community Social Vulnerability Indicators (CSVIs) were developed using secondary data including social, demographic and fisheries variables. The social and demographic data were downloaded from the 2014 American Community Survey (ACS) 5-yr estimates Dataset at the U.S. Census American FactFinder site for coastal communities at the Census Designated Place (CDP) level, and in some cases the County Subdivision (MCD) level. Commercial fisheries data were pulled from the SOLE server located at Northeast Fisheries Science Center in Woods Hole, MA. The recreational fishing information is publicly accessible through the Marine Recreational Information Program (MRIP), and for this analysis was custom requested from NOAA Fisheries headquarters.

12.1.2 Data extraction

Commercial fisheries data was pulled from the NEFSC SOLE server in Woods Hole, MA.

SQL and SAS code for data extraction and processing steps can be found [here](#).

12.1.3 Data analysis

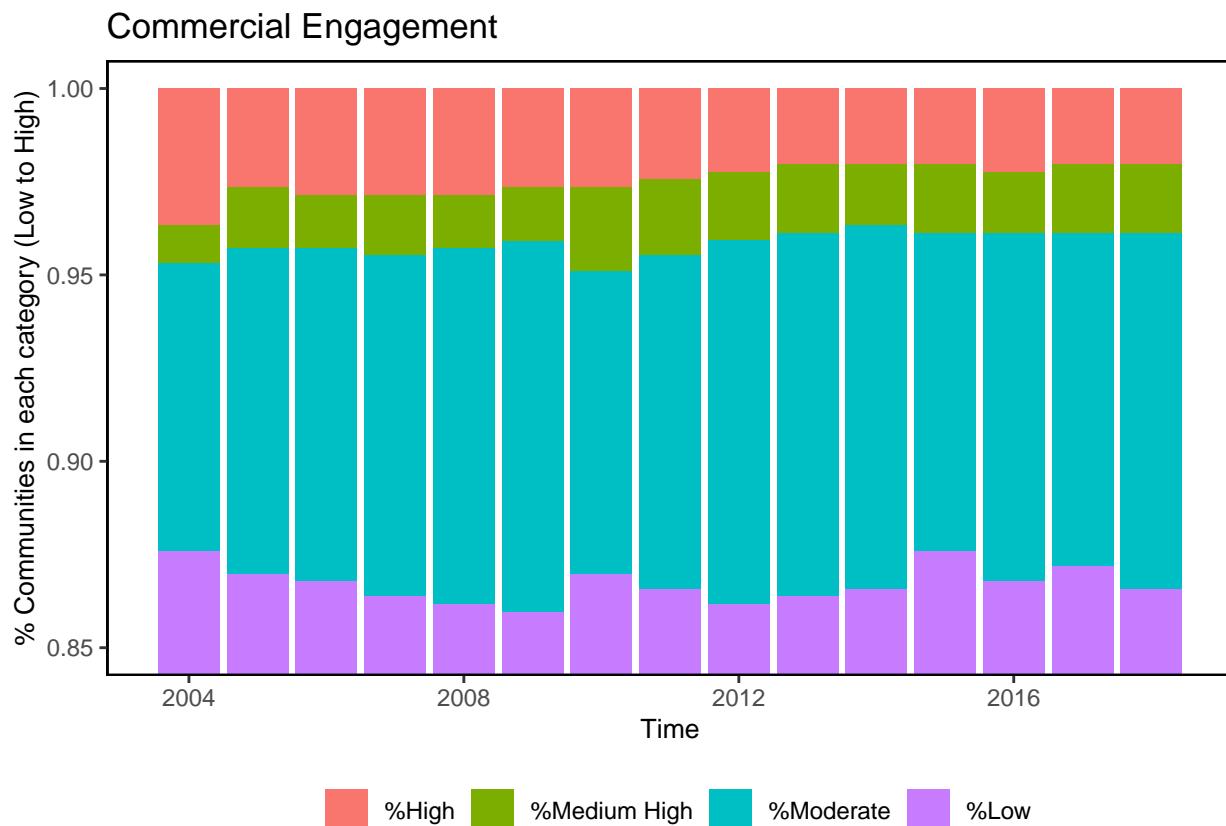
The indicators were developed using the methodology described in Jacob et al. (2010), Jacob et al. (2013), Colburn and Jepson (2012) and Jepson and Colburn (2013). Indicators were constructed through principal component analysis with a single factor solution, and the following criteria had to have been met: a minimum variance explained of 45%; Kaiser-Meyer Olkin measure of sampling adequacy above .500; factor loadings above .350; Bartlett's test of sphericity significance above .05; and an Armor's Theta reliability coefficient above .500. Factor scores for each community were ranked based on standard deviations into the following categories: High ($>=1.00\text{SD}$), MedHigh (.500-.999 SD), Moderate (.000-.499 SD) and Low ($<.000\text{ SD}$).

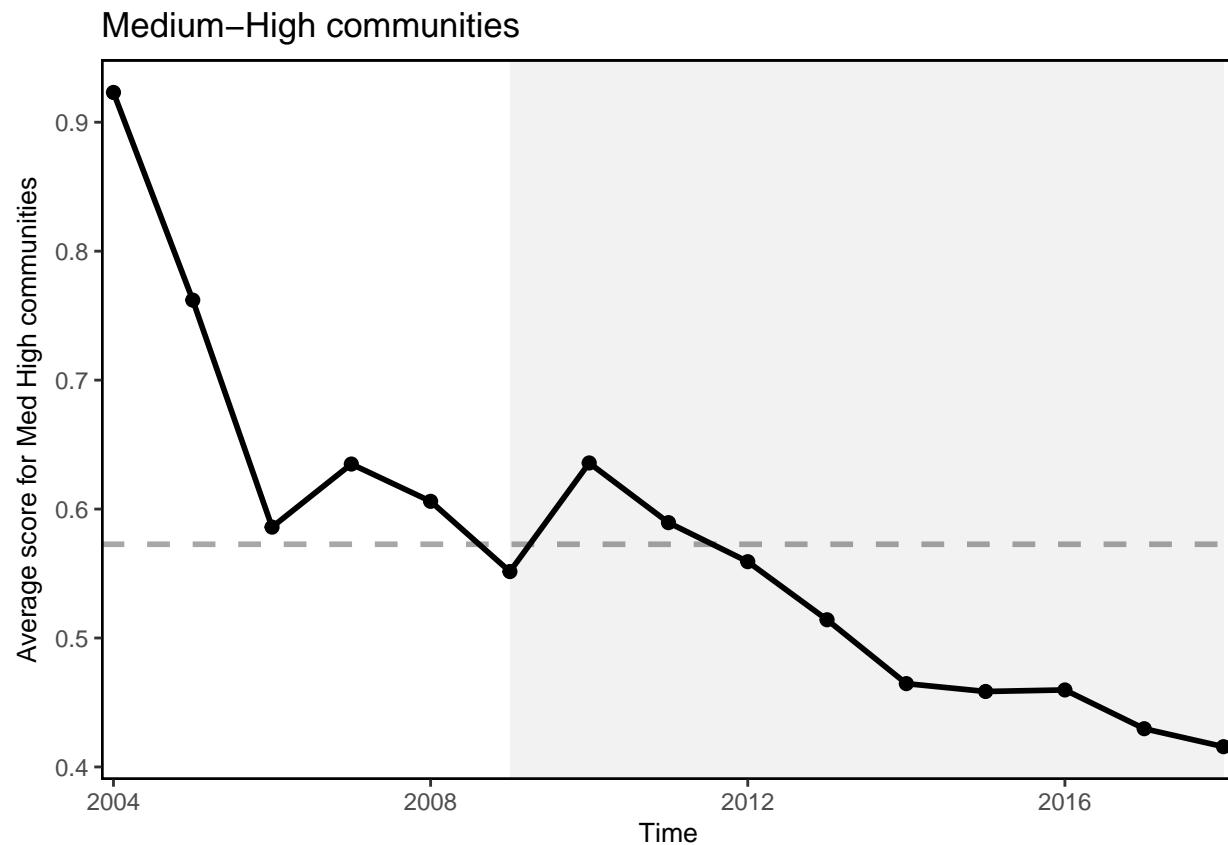
12.1.4 Data processing

Data were formatted for inclusion in the ecodata R package using the R script found [here](#).

12.1.5 Plotting

Code used to build the community engagement indicator plot below can be found [here](#).





Chapter 13

Conceptual Models

Description: Conceptual models for the New England (Georges Bank and Gulf of Maine) and Mid-Atlantic regions of the Northeast US Large Marine Ecosystem

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018, 2019, 2020), State of the Ecosystem - Mid-Atlantic (2018, 2019, 2020)

Indicator category: Synthesis of published information, Extensive analysis; not yet published

Contributor(s): Sarah Gaichas, Patricia Clay, Geret DePiper, Gavin Fay, Michael Fogarty, Paula Fratantoni, Robert Gamble, Sean Lucey, Charles Perretti, Patricia Pinto da Silva, Vincent Saba, Laurel Smith, Jamie Tam, Steve Traynor, Robert Wildermuth

Data steward: Sarah Gaichas, sarah.gaichas@noaa.gov

Point of contact: Sarah Gaichas, sarah.gaichas@noaa.gov

Public availability statement: All source data aside from confidential commercial fisheries data (relevant only to some components of the conceptual models) are available to the public (see Data Sources below).

13.1 Methods

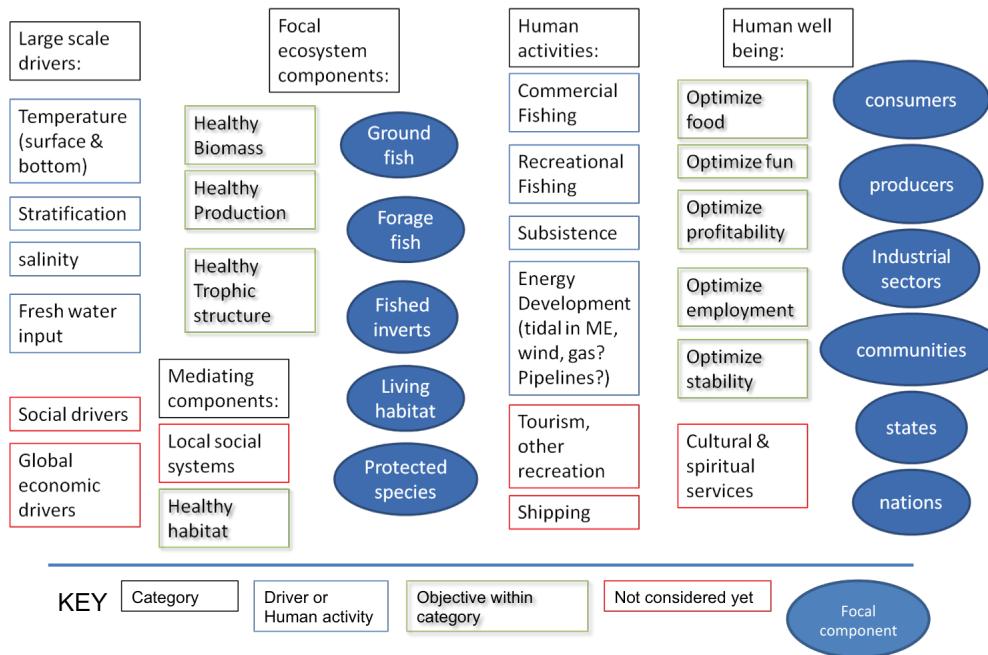
Conceptual models were constructed to facilitate multidisciplinary analysis and discussion of the linked social-ecological system for integrated ecosystem assessment. The overall process was to first identify the components of the model (focal groups, human activities, environmental drivers, and objectives), and then to document criteria for including groups and linkages and what the specific links were between the components.

The prototype conceptual model used to design Northeast US conceptual models for each ecosystem production unit (EPU) was designed by the California Current IEA program. The California Current IEA developed an overview conceptual model for the Northern California Current Large Marine Ecosystem (NCC), with models for each focal ecosystem component that detailed the ecological, environmental, and human system linkages. Another set of conceptual models outlined habitat linkages.

An initial conceptual model for Georges Bank and the Gulf of Maine was outlined at the 2015 ICES WGNARS meeting. It specified four categories: Large scale drivers, focal ecosystem components, human activities, and human well being. Strategic management objectives were included in the conceptual model, which had not been done in the NCC. Focal ecosystem components were defined as aggregate species groups that had associated US management objectives (outlined within WGNARS for IEAs, see DePiper et al. (2017)): groundfish, forage fish, fished invertebrates, living habitat, and protected species. These categories roughly align with Fishery Management Plans (FMPs) for the New England Fishery Management Council. The

Mid-Atlantic conceptual model was developed along similar lines, but the focal groups included demersals, forage fish, squids, medium pelagics, clams/quahogs, and protected species to better align with the Mid Atlantic Council's FMPs.

First draft IEA Conceptual Model: Georges Bank Gulf of Maine



After the initial draft model was outlined, working groups were formed to develop three submodels following the CCE example: ecological, environmental, and human dimensions. The general approach was to specify what was being included in each group, what relationship was represented by a link between groups, what threshold of the relationship was used to determine whether a relationship was significant enough to be included (we did not want to model everything), the direction and uncertainty of the link, and documentation supporting the link between groups. This information was recorded in a spreadsheet. Submodels were then merged together by common components using the “merge” function in the (currently unavailable) desktop version of Mental Modeler (<http://www.mentalmodeler.org/#home>; Gray et al. (2013)). The process was applied to Georges Bank (GB), the Gulf of Maine (GOM), and the Mid-Atlantic Bight (MAB) Ecological Production Units.

13.1.1 Data sources

13.1.1.1 Ecological submodels

Published food web (EMAX) models for each subregion (J.S. Link et al. 2006; Link et al. 2008), food habits data collected by NEFSC trawl surveys (Smith and Link 2010), and other literature sources (Smith et al. 2015) were consulted. Expert judgement was also used to adjust historical information to current conditions, and to include broad habitat linkages to Focal groups.

13.1.1.2 Environmental submodels

Published literature on the primary environmental drivers (seasonal and interannual) in each EPU was consulted. Sources for Georges Bank included Backus and Bourne (1987) and Townsend et al. (2006). Sources for the Gulf of Maine included Smith (1983), Smith et al. (2001), Mupparapu and Brown (2002), Townsend et al. (2006), Smith et al. (2012), and Mountain (2012).

Sources for the Mid Atlantic Bight included Houghton et al. (1982), Beardsley et al. (1985), Lentz (2003), Mountain (2003), Glenn et al. (2004), Sullivan, Cowen, and Steves (2005), Castelao et al. (2008), Shearman and Lentz (2009), Castelao, Glenn, and Schofield (2010), Gong, Kohut, and Glenn (2010), Gawarkiewicz et al. (2012), Forsyth, Andres, and Gawarkiewicz (2015), Fratantoni, Holzwart-Davis, and Taylor (2015), Zhang and Gawarkiewicz (2015), Timothy J. Miller, Hare, and Alade (2016), and Lentz (2017).

13.1.1.3 Human dimensions submodels

Fishery catch and bycatch information was drawn from multiple regional datasets, including the Greater Atlantic Regional Office Vessel Trip Reports & Commercial Fisheries Dealer databases, Northeast Fishery Observer Program & Northeast At-Sea Monitoring databases, Northeast Fishery Science Center Social Sciences Branch cost survey, and the Marine Recreational Informational Program database. Further synthesis of human welfare derived from fisheries was drawn from Färe, Kirkley, and Walden (2006), Walden et al. (2012), Lee and Thunberg (2013), Lee (2014), and Lee, Steinback, and Wallmo (2017). Bycatch of protected species was taken from Waring et al. (2015), with additional insights from Bisack and Magnusson (2014). The top 3 linkages were drawn for each node. For example, the top 3 recreational species for the Mid-Atlantic were used to draw linkages between the recreational fishery and species focal groups. A similar approach was used for relevant commercial fisheries in each region.

Habitat-fishery linkages were drawn from unpublished reports, including:

1. Mid-Atlantic Fishery Management Council. 2016. Amendment 16 to the Atlantic Mackerel, Squid, and Butterfish Fishery Management Plan: Measures to protect deep sea corals from Impacts of Fishing Gear. Environmental Assessment, Regulatory Impact Review, and Initial Regulatory Flexibility Analysis. Dover, DE. August, 2016.
2. NOAA. 2016. Deep sea coral research and technology program 2016 Report to Congress. <http://www.habitat.noaa.gov/protection/corals/deepseacorals.html> retrieved February 8, 2017.
3. New England Fishery Management Council. 2016. Habitat Omnibus Deep-Sea Coral Amendment: Draft. <http://www.nefmc.org/library/omnibus-deep-sea-coral-amendment> Retrieved Feb 8, 2017.
4. Bachman et al. 2011. The Swept Area Seabed Impact (SASI) Model: A Tool for Analyzing the Effects of Fishing on Essential Fish Habitat. New England Fisheries Management Council Report. Newburyport, MA.

Tourism and habitat linkages were drawn from unpublished reports, including:

1. <http://neers.org/RESOURCES/Bibliographies.html>
2. Great Bay (GoM) resources <http://greatbay.org/about/publications.htm>
3. Meaney, C.R. and C. Demarest. 2006. Coastal Polution and New England Fisheries. Report for the New England Fisheries Management Council. Newburyport, MA.
4. List of valuation studies, by subregion and/or state, can be found at <http://www.oceaneconomics.org/nonmarket/valestim.asp>.

Published literature on human activities in each EPU was consulted.

Sources for protected species and tourism links included Hoagland and Meeks (2000) and Lee (2010).

Sources for links between environmental drivers and human activities included Adams (1973), Matzarakis and Freitas (2001), Scott, McBoyle, and Schwartzenruber (2004), Hess, Malilay, and Parkinson (2008), Colburn and Jepson (2012), Jepson and Colburn (2013), and Colburn et al. (2016).

Sources for cultural practices and attachments links included Pauly (1997), McGoodwin (2001), St Martin (2001), Norris-Raynbird (2004), Pollnac et al. (2006), Clay and Olson (2007), Clay and Olson (2008), Everett and Aitchison (2008), Donkersloot (2010), Lord (2011), Halpern et al. (2012), Wynveen, Kyle, and

Sutton (2012), Cortes-Vazquez and Zedalis (2013), Koehn, Reineman, and Kittinger (2013), Potschin and Haines-Young (2013), Reed et al. (2013), Urquhart and Acott (2013), Blasiak et al. (2014), Klain, Satterfield, and Chan (2014), Poe, Norman, and Levin (2014), Brown (2015), Donatuto and Poe (2015), Khakzad and Griffith (2016), Oberg et al. (2016), and Seara, Clay, and Colburn (2016).

13.1.2 Data extraction

13.1.2.1 Ecological submodels

“Data” included model estimated quantities to determine whether inclusion thresholds were met for each potential link in the conceptual model. A matrix with diet composition for each modeled group is an input to the food web model. A matrix of mortalities caused by each predator and fishery on each modeled group is a direct output of a food web model (e.g. Ecopath). Food web model biomass flows between species, fisheries, and detritus were summarized using algorithms implemented in visual basic by Kerim Aydin, NOAA NMFS Alaska Fisheries Science Center. Because EMAX model groups were aggregated across species, selected diet compositions for individual species were taken from the NEFSC food habits database using the FEAST program for selected species (example query below). These diet queries were consulted as supplemental information.

Example FEAST sql script for Cod weighted diet on Georges Bank can be found [here](#). Queries for different species are standardized by the FEAST application and would differ only in the svsp code.

13.1.2.2 Environmental submodels

Information was synthesized entirely from published sources and expert knowledge; no additional data extraction was completed for the environmental submodels.

13.1.2.3 Human dimensions submodels

Recreational fisheries data were extracted from the 2010-2014 MRIP datasets. Original data can be found here for each region (New England or Mid-Atlantic as defined by states).

Commercial fishing data was developed as part of the State of the Ecosystem Report, including revenue and food production estimates, with data extraction methodology discussed in the relevant sections of the technical document. In addition, the Northeast Regional Input/Output Model (Steinback and Thunberg 2006) was used as the basis for the strength of the employment linkages.

13.1.3 Data analysis

13.1.3.1 Ecological submodels

Aggregated diet and mortality information was examined to determine the type of link, direction of link, and which links between which groups should be included in the conceptual models. Two types of ecological links were defined using food web models: prey links and predation/fishing mortality links. Prey links resulted in positive links between the prey group and the focal group, while predation/fishing mortality links resulted in negative links to the focal group to represent energy flows. The intent was to include only the most important linkages between focal groups and with other groups supporting or causing mortality on focal species groups. Therefore, threshold levels of diet and mortality were established (based on those that would select the top 1-3 prey and predators of each focal group): 10% to include a link (or add a linked group) in the model and 20% to include as a strong link. A Primary Production group was included in each model and linked to pelagic habitat to allow environmental effects on habitat to be connected to the ecological submodel. Uncertainty for the inclusion of each link and for the magnitude of each link was qualitatively assessed and noted in the spreadsheet.

Four habitat categories (Pelagic, Seafloor and Demersal, Nearshore, and Freshwater and Estuarine) were included in ecological submodels as placeholders to be developed further along with habitat-specific research. Expert opinion was used to include the strongest links between each habitat type and each Focal group (noting that across species and life stages, members of these aggregate groups likely occupy many if not all of the habitat types). Link direction and strength were not specified. Environmental drivers were designed to link to habitats, rather than directly to Focal groups, to represent each habitat's important mediation function.

EMAX model groups were aggregated to focal groups for the Georges Bank (GB), Gulf of Maine (GOM) and Mid-Atlantic Bight (MAB) conceptual models according to Table 13.1. “Linked groups” directly support or impact the Focal groups as described above.

Table 13.1: Relationship between food web model groups and conceptual model focal groups. Pinnipeds not included in GB and Seabirds not included in MAB.

Group	Type	Region	Conceptual model group	EMAX group(s)
Focal	GB		Commercial Fishery	Fishery
Focal	GB		Fished Inverts	Megabenthos filterers
Focal	GB		Forage Fish	Sum of Small pelagics-commercial, other, anadromous, and squids
Focal	GB		Groundfish	Sum of Demersals-omnivores, benthivores, and piscivores
Focal	GB		Protected Species	Sum of Baleen Whales, Odontocetes, and Seabirds
Linked	GB		Benthos	Sum of Macrobenthos-polychaetes, crustaceans, molluscs, other and Megabenthos-other
Linked	GB		Copepods and Micronecton	Sum of Copepods-small and large, and Micronekton
Linked	GB		Detritus and Bacteria	Sum of Bacteria and Detritus-POC
Linked	GB		Gelatinous zooplankton	Gelatinous zooplankton
Linked	GB		Primary Production	Phytoplankton-Primary production
Focal	GOM		Commercial Fishery	Fishery
Focal	GOM		Fished Inverts	Megabenthos filterers
Focal	GOM		Forage Fish	Sum of Small pelagics-commercial, other, anadromous, and squids
Focal	GOM		Groundfish	Sum of Demersals-omnivores, benthivores, and piscivores
Focal	GOM		Protected Species	Sum of Baleen Whales, Odontocetes, Pinnipeds, and Seabirds
Linked	GOM		Benthos	Sum of Macrobenthos-polychaetes, crustaceans, molluscs, other and Megabenthos-other
Linked	GOM		Copepods and Micronecton	Sum of Copepods-small and large, and Micronekton
Linked	GOM		Detritus and Bacteria	Sum of Bacteria and Detritus-POC
Linked	GOM		Gelatinous zooplankton	Gelatinous zooplankton
Linked	GOM		Primary Production	Phytoplankton-Primary production
Focal	MAB		Clams Quahogs	Megabenthos filterers
Focal	MAB		Commercial Fishery	Fishery
Focal	MAB		Demersals	Sum of Demersals-omnivores, benthivores, and piscivores
Focal	MAB		Forage Fish	Sum of Small pelagics-commercial, other, and anadromous
Focal	MAB		Medium Pelagics	Medium pelagics
Focal	MAB		Protected Species	Sum of Baleen whales and Odontocetes
Focal	MAB		Squids	Small pelagics-squids
Linked	MAB		Benthos	Sum of Macrobenthos-polychaetes, crustaceans, molluscs, other
Linked	MAB		Copepods and Micronecton	Sum of Copepods-small and large, and Micronekton
Linked	MAB		Detritus and Bacteria	Sum of Bacteria and Detritus-POC
Linked	MAB		Gelatinous zooplankton	Gelatinous zooplankton
Linked	MAB		Primary Production	Phytoplankton-Primary production
Linked	MAB		Sharks	Sum of Sharks-pelagic and coastal

Ecological submodels were constructed and visualized in Mental Modeler (Fig. 13.1). Here, we show only the Gulf of Maine submodels as examples.

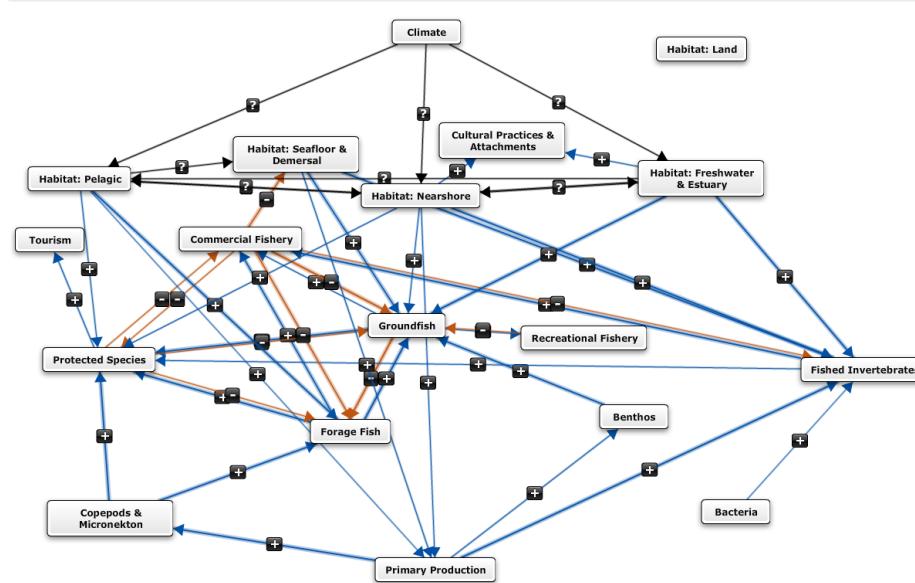


Figure 13.1: Gulf of Maine Ecological submodel

13.1.3.2 Environmental submodels

Environmental submodels were designed to link key oceanographic processes in each ecosystem production unit to the four general habitat categories (Pelagic, Seafloor and Demersal, Nearshore, and Freshwater and Estuarine) with emphasis on the most important physical processes in each ecosystem based on expert knowledge as supported by literature review. The basis of each submodel were environmental variables observable at management-relevant scales as identified by WGNARS: Surface and Bottom Water Temperature and Salinity, Freshwater Input, and Stratification (as well as sea ice timing and cover, which is not relevant to the northeast US shelf). Key drivers changing these observable variables and thus structuring habitat dynamics in each Ecological Production Units were added to the model using expert consensus.

Environmental submodels were initially constructed and visualized in Mental Modeler (Fig. 13.2).

13.1.3.3 Human dimensions submodels

The top 3 species from each mode of recreational fishing (shoreside, private boat, party/charter) were used to assess the potential for missing links between the recreational fishing activity and biological focal components. Given the predominance of Mid-Atlantic groundfish in recreational fishing off New England (summer flounder, bluefish, striped bass), a Mid-Atlantic groundfish focal component was added to the Georges Bank EPU model. The magnitude of benefits generated from recreational fishing was scaled to reflect expert knowledge of target species, coupled with the MRIP data highlighted above. Scales were held consistent across the focal components within recreational fishing.

No additional biological focal components were added to the commercial fishing activity, beyond what was developed in the ecological submodel. Benefits derived from commercial fishing were scaled to be consistent with the State of the Ecosystem revenue estimates, as modulated by expert knowledge and additional data sources. For example, the percentage of landings sold as food was used to map fishing activity to the commercial fishery food production objective, and the Northeast Regional Input/Output Model (Steinback

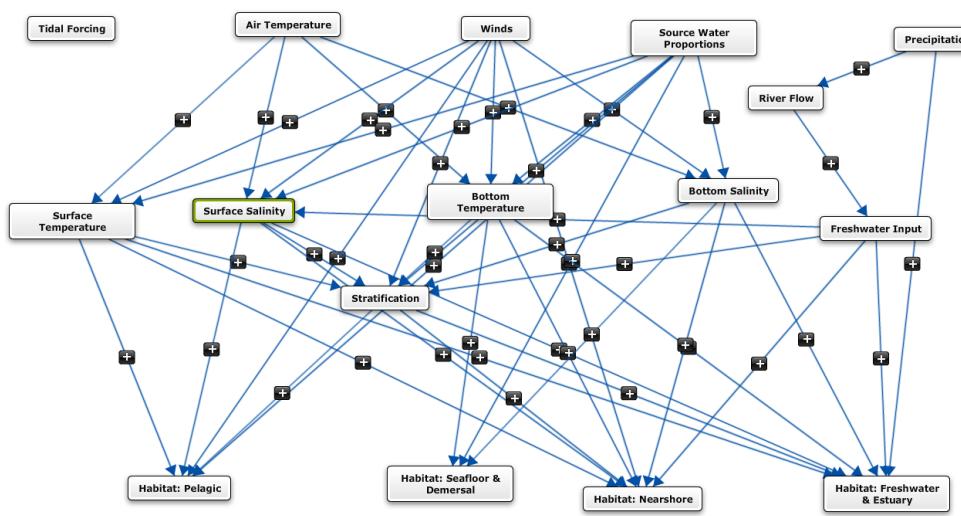


Figure 13.2: Gulf of Maine Environmental submodel

and Thunberg 2006) was used to define the strength of the employment linkages. For profitability, expert knowledge was used to reweight revenue landings, based on ancillary cost data available (Das, Chhandita 2013, 2014). Human activities and objectives for the conceptual sub model are defined in DePiper et al. (2017). As shown in Figure 13.3, human dimensions submodels were also initially constructed and visualized in Mental Modeler.

13.1.3.4 Merged models

All links and groups from each submodel were preserved in the full merged model for each system. Mental modeler was used to merge the submodels. Full models were then re-drawn in Dia (<http://dia-installer.de/>) with color codes for each model component type for improved readability. Examples for each system are below.

13.1.3.5 Communication tools

The merged models were redrawn for use in communications with the public. These versions lead off the State of the Ecosystem reports for both Fishery Management Councils to provide an overview of linkages between environmental drivers, ecological, and human systems.

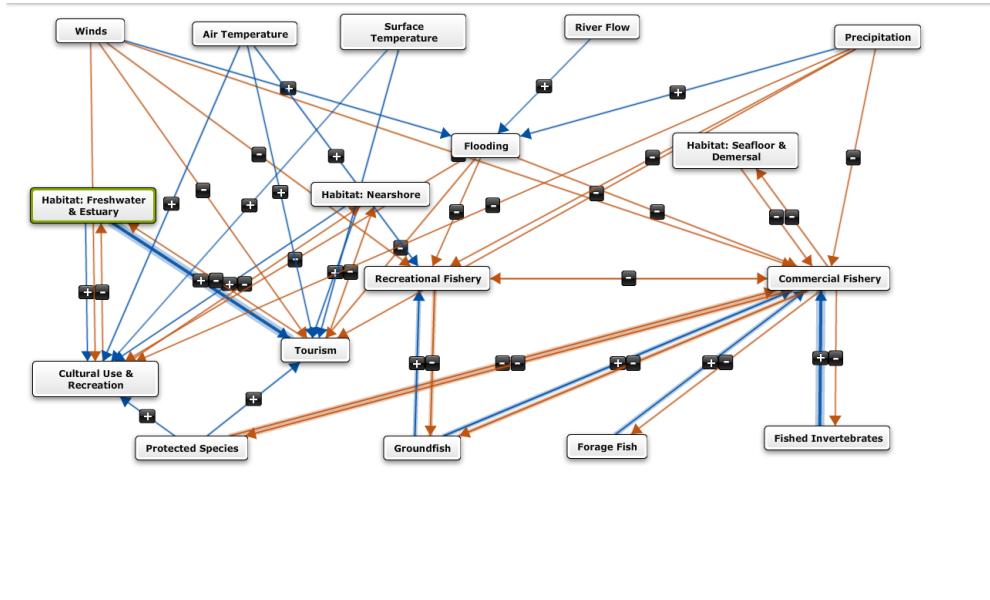


Figure 13.3: Gulf of Maine Human dimensions submodel

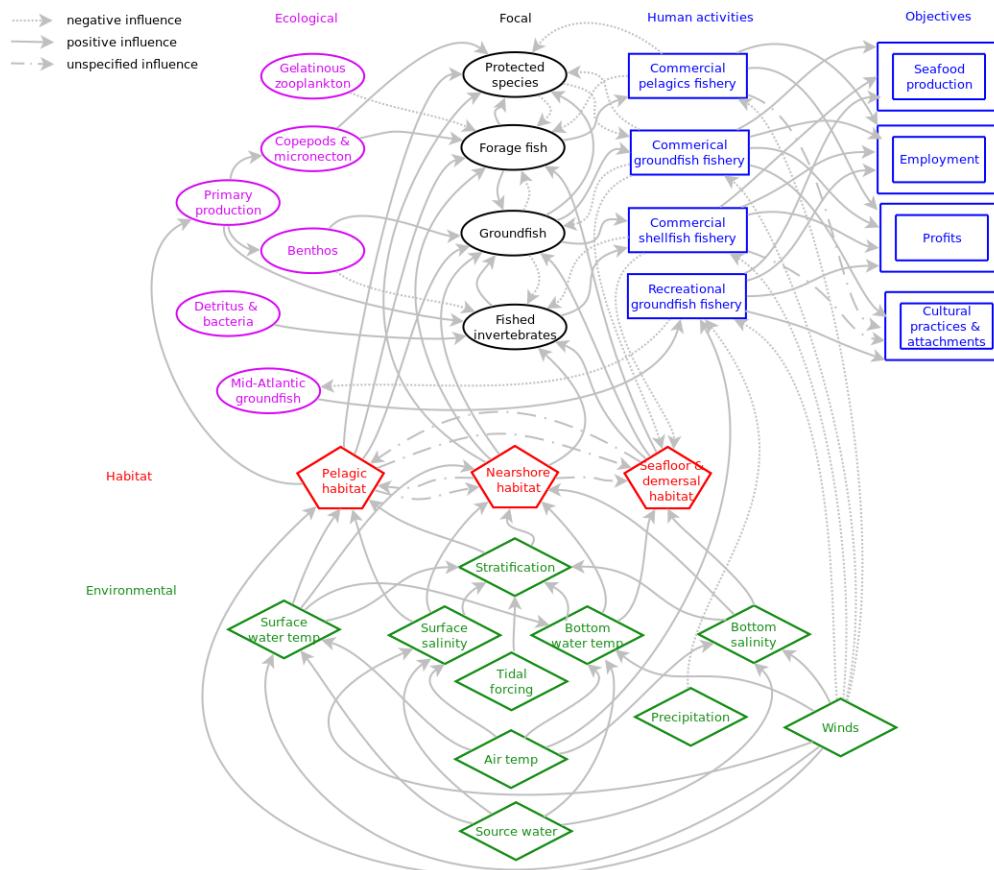


Figure 13.4: Georges Bank conceptual model

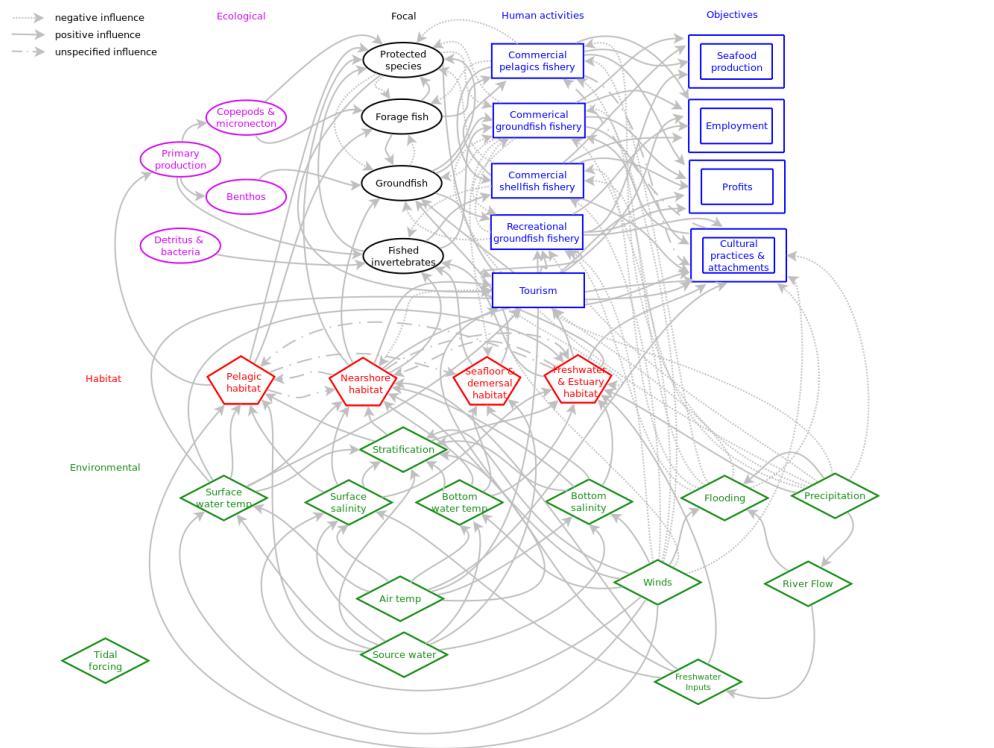


Figure 13.5: Gulf of Maine conceptual model

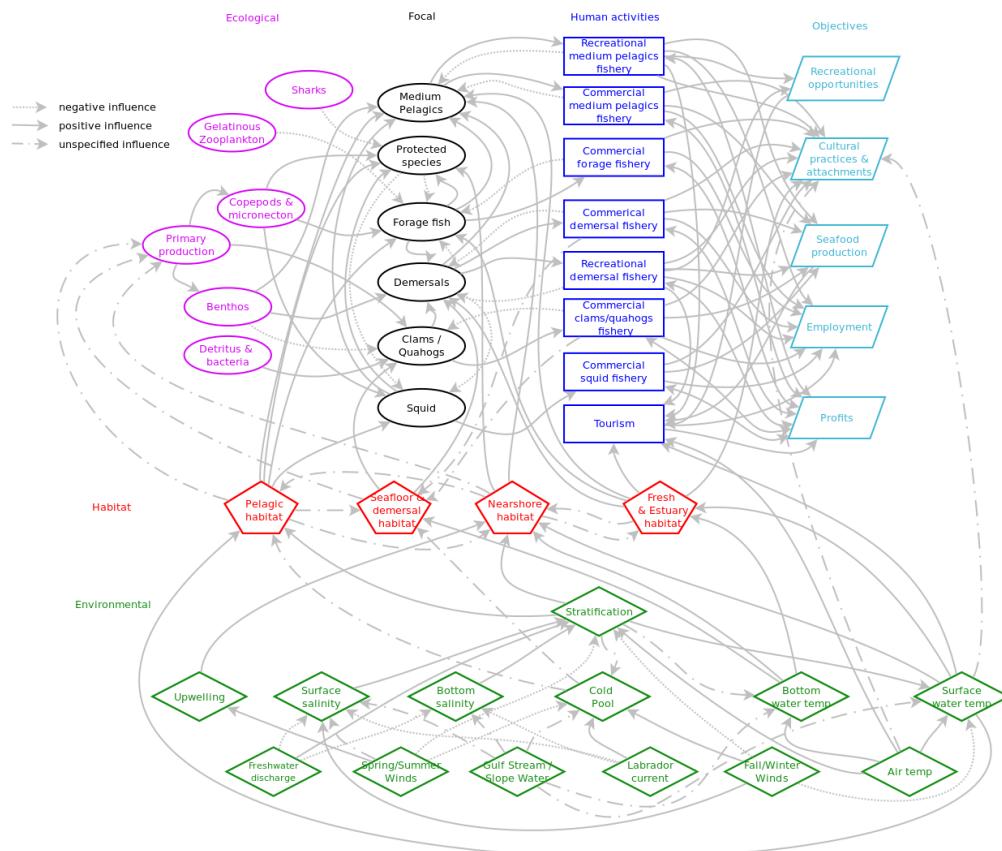


Figure 13.6: Mid-Atlantic Bight conceptual model

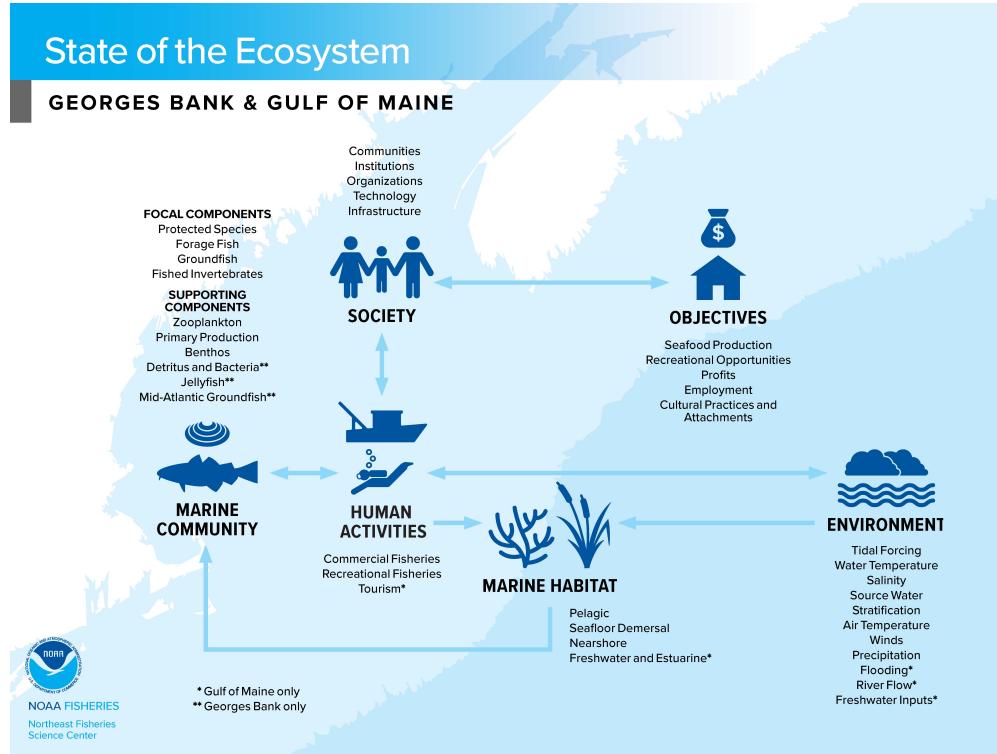


Figure 13.7: New England conceptual model for public communication

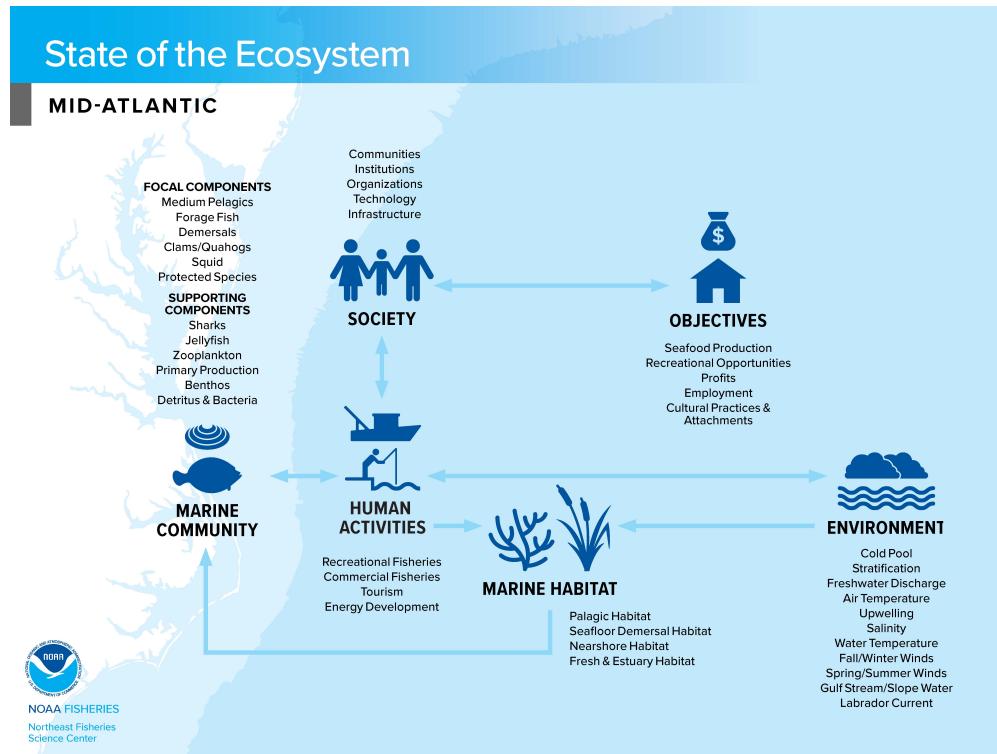


Figure 13.8: Mid-Atlantic conceptual model for public communication

Chapter 14

Fish Condition Indicator

Description: Relative condition

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018,2019, 2020), State of the Ecosystem - Mid-Atlantic (2018,2019, 2020)

Indicator category: Database pull with analysis

Contributor(s): Laurel Smith

Data steward: Laurel Smith, laurel.smith@noaa.gov

Point of contact: Laurel Smith, laurel.smith@noaa.gov

Public availability statement: NEFSC survey data used in these analyses are available upon request (see BTS metadata for access procedures). Derived condition data are available here.

14.1 Methods

Relative condition (Kn) was introduced by Cren (1951) as a way to remove the influence of length on condition, and Blackwell, Brown, and Willis (2000) noted that Kn may be useful in detecting prolonged physical stress on a fish populations. Relative condition is calculated as

$$Kn = W/W',$$

where W is the weight of an individual fish and W' is the predicted length-specific mean weight for the fish population in a given region. "Here, relative condition was calculated for finfish stocks commonly caught on the Northeast Fisheries Science Center's (NEFSC) autumn and spring bottom trawl surveys, from 1992-present.

Where data allowed, predicted length-weight parameters were calculated for W' by species, sex and season over the time period 1992-2012. When sample sizes of individual fish weights and lengths were too low, parameters were calculated for aggregated spring and fall survey data over the same time period. Fall survey relative condition was calculated by sex for those species that exhibited differences in growth between sexes and aggregated across sex for those that did not.

The Condition package used for calculations and plotting of fish condition factor can be found on GitHub.

14.1.1 Data sources

Individual fish lengths (to the nearest 0.5 cm) and weights (grams) were collected on the NEFSC bottom trawl surveys from 1992-present aboard RVs Albatross IV, Delaware II and the Henry B. Bigelow (see Survdat). A

small number of outlier values were removed when calculating the length-weight parameters.

14.1.2 Data extraction

Data were extracted from NEFSC's survey database (SVDBS) using the R script found [here](#)

14.1.3 Data analysis

The following growth curve was fit through individual fish lengths and weights from the NEFSC bottom trawl survey data from 1992-2012 to produce reference length-weight parameters:

$$\text{Weight} = e^{Fall_{coef}} * \text{Length}^{Fall_{exp}},$$

where length is in cm and weight is in kg. Fall survey data were used where sample sizes allowed for growth curve estimation, otherwise data from spring and fall seasons were combined.

Individual fish lengths from NEFSC fall bottom trawl survey from 1992-2017 were then used to calculate predicted weights using the reference length-weight parameters. Relative condition (Kn) was calculated annually by species and sex (for sexually dimorphic species) by dividing individual fish weights by the predicted weight.

The code found [here](#) was used in the analysis of fish condition.

14.1.4 Plotting

Code for plotting the fish condition indicator can be found [here](#).

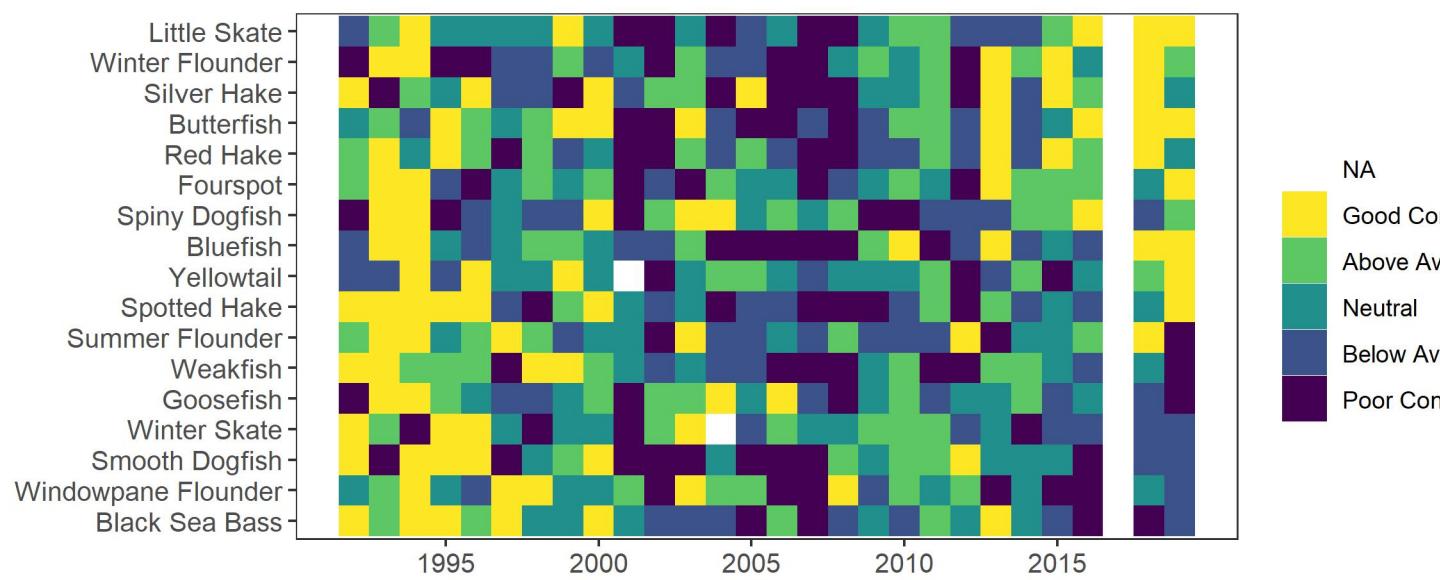


Figure 14.1: Condition factor for fish species in the MAB. MAB data are missing for 2017 due to survey delays.

Chapter 15

Ecological Production Units

Description: Ecological Production Units

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018, 2019, 2020), State of the Ecosystem - Mid-Atlantic (2018, 2019, 2020)

Indicator category: Extensive analysis, not yet published

Contributor(s): Robert Gamble

Data steward: NA

Point of contact: Robert Gamble, robert.gamble@noaa.gov

Public availability statement: Ecological production unit (EPU) shapefiles are available [here](#). More information about source data used to derive EPUs can be found [here](#).

15.1 Methods

To define ecological production units (EPUs), we assembled a set of physiographic, oceanographic and biotic variables on the Northeast U.S. Continental Shelf, an area of approximately 264,000 km² within the 200 m isobath. The physiographic and hydrographic variables selected have been extensively used in previous analyses of oceanic provinces and regions (e.g Roff and Taylor 2000). Primary production estimates have also been widely employed for this purpose in conjunction with physical variables (Longhurst 2007) to define ecological provinces throughout the world ocean.

We did not include information on zooplankton, benthic invertebrates, fish, protected species, or fishing patterns in our analysis. The biomass and production of the higher trophic level groups in this region has been sharply perturbed by fishing and other anthropogenic influences. Similarly, fishing patterns are affected by regulatory change, market and economic factors and other external influences.

Because these malleable patterns of change are often unconnected with underlying productivity, we excluded factors directly related to fishing practices. The physiographic variables considered in this analysis are listed in Table 15.1. They include bathymetry and surficial sediments. The physical oceanographic and hydrographic measurements include sea surface temperature, annual temperature span, and temperature gradient water derived from satellite observations for the period 1998 to 2007.

Table 15.1: Variables used in derivation of Ecological Production Units.

Variables	Sampling Method	Units
Surficial Sediments	Benthic Grab	Krumbian Scale
Sea Surface Temperature	Satellite Imagery (4km grid)	°C annual average
Sea Surface Temperature	Satellite Imagery (4km grid)	dimensionless
Sea Surface Temperature	Satellite Imagery (4km grid)	°C annual average
Surface Temperature	Shipboard hydrography (point)	°C (Spring and Fall)
Bottom Temperature	Shipboard hydrography (point)	°C (Spring and Fall)
Surface Salinity	Shipboard hydrography (point)	psu (Spring and Fall)
Bottom Salinity	Shipboard hydrography (point)	psu (Spring and Fall)
Stratification	Shipboard hydrography (point)	Sigma-t units (Spring and Fall)
Chlorophyll-a	Satellite Imagery (1.25 km grid)	mg/C/m^3 (annual average)
Chlorophyll-a gradient	Satellite Imagery (1.25 km grid)	dimensionless
Chlorophyll-a span	Satellite Imagery (1.25 km grid)	mg/C/m^3 (annual average)
Primary Production	Satellite Imagery (1.25 km grid)	gC/m^3/year (cumulative)
Primary Production gradient	Satellite Imagery (1.25 km grid)	dimensionless
Primary Production span	Satellite Imagery (1.25 km grid)	gC/m^3/year (cumulative)

15.1.1 Data sources

Shipboard observations for surface and bottom water temperature and salinity in surveys conducted in spring and fall. Daily sea surface temperature (SST, °C) measurements at 4 km resolution were derived from nighttime scenes composited from the AVHRR sensor on NOAA’s polar-orbiting satellites and from NASA’s MODIS TERRA and MODIS AQUA sensors. We extracted information for the annual mean SST, temperature span, and temperature gradients from these sources. The latter metric provides information on frontal zone locations.

The biotic measurements included satellite-derived estimates of chlorophyll *a* (CHLa) mean concentration, annual span, and CHLa gradients and related measures of primary production. Daily merged SeaWiFS/MODIS-Aqua CHLa (CHL, mg m⁻³) and SeaWiFS photosynthetically available radiation (PAR, Einsteins m⁻² d⁻¹) scenes at 1.25 km resolution were obtained from NASA Ocean Biology Processing Group.

15.1.2 Data extraction

NA

15.1.3 Data analysis

In all cases, we standardized the data to common spatial units by taking annual means of each observation type within spatial units of 10' latitude by 10' longitude to account for the disparate spatial and temporal scales at which these observations are taken. There are over 1000 spatial cells in this analysis. Shipboard sampling used to obtain direct hydrographic measurements is constrained by a minimum sampling depth of 27 m specified on the basis of prescribed safe operating procedures. As a result nearshore waters are not fully represented in our initial specifications of ecological production units.

The size of the spatial units employed further reflects a compromise between retaining spatial detail and minimizing the need for spatial interpolation of some data sets. For shipboard data sets characterized by relatively coarse spatial resolution, where necessary, we first constructed an interpolated map using an inverse distance weighting function before including it in the analysis. Although alternative interpolation schemes

based on geostatistical approaches are possible, we considered the inverse distance weighting function to be both tractable and robust for this application.

We first employed a spatial principal components analysis (PCA; e.g. Pielou 1984; Legendre and Legendre 1998) to examine the multivariate structure of the data and to account for any inter-correlations among the variables to be used in subsequent analysis. The variables included in the analysis exhibited generally skewed distributions and we therefore transformed each to natural logarithms prior to analysis.

The PCA was performed on the correlation matrix of the transformed observations. We selected the eigenvectors associated with eigenvalues of the dispersion matrix with scores greater than 1.0 (the Kaiser-Guttman criterion; Legendre and Legendre 1998) for all subsequent analysis. These eigenvectors represent orthogonal linear combinations of the original variables used in the analysis.

We delineated ecological subunits by applying a disjoint cluster based on Euclidean distances using the K-means procedure (Legendre and Legendre 1998) on the principal component scores. The use of non-independent variables can strongly influence the results of classification analyses of this type (Pielou 1984), hence the interest in using the PCA results in the cluster.

The eigenvectors were represented as standard normal deviates. We used a Pseudo-F Statistic described by Milligan and Cooper (1985) to objectively define the number of clusters to use in the analysis. The general approach employed is similar to that of Host et al. (1996) for the development of regional ecosystem classifications for terrestrial systems.

After the analyses were done, we next considered options for interpolation of nearshore boundaries resulting from depth-related constraints on shipboard observations. For this, we relied on information from satellite imagery. For the missing nearshore areas in the Gulf of Maine and Mid-Atlantic Bight, the satellite information for chlorophyll concentration and sea surface temperature indicated a direct extension from adjacent observations. For the Nantucket Shoals region south of Cape Cod, similarities in tidal mixing patterns reflected in chlorophyll and temperature observations indicated an affinity with Georges Bank and the boundaries were changed accordingly.

Finally, we next considered consolidation of ecological subareas so that nearshore regions are considered to be special zones nested within the adjacent shelf regions. Similar consideration led to nesting the continental slope regions within adjacent shelf regions in the Mid-Atlantic and Georges Bank regions. This led to four major units: Mid-Atlantic Bight, Georges Bank, Western-Central Gulf of Maine (simply “Gulf of Maine” in the State of the Ecosystem), and Scotian Shelf-Eastern Gulf of Maine. As the State of the Ecosystem reports are specific to FMC managed regions, the Scotian Shelf-Eastern Gulf of Maine EPU is not considered in SOE indicator analyses.

15.1.4 Data processing

Shapefiles were converted to `sf` objects for inclusion in the `ecodata` R package using the R code found here.

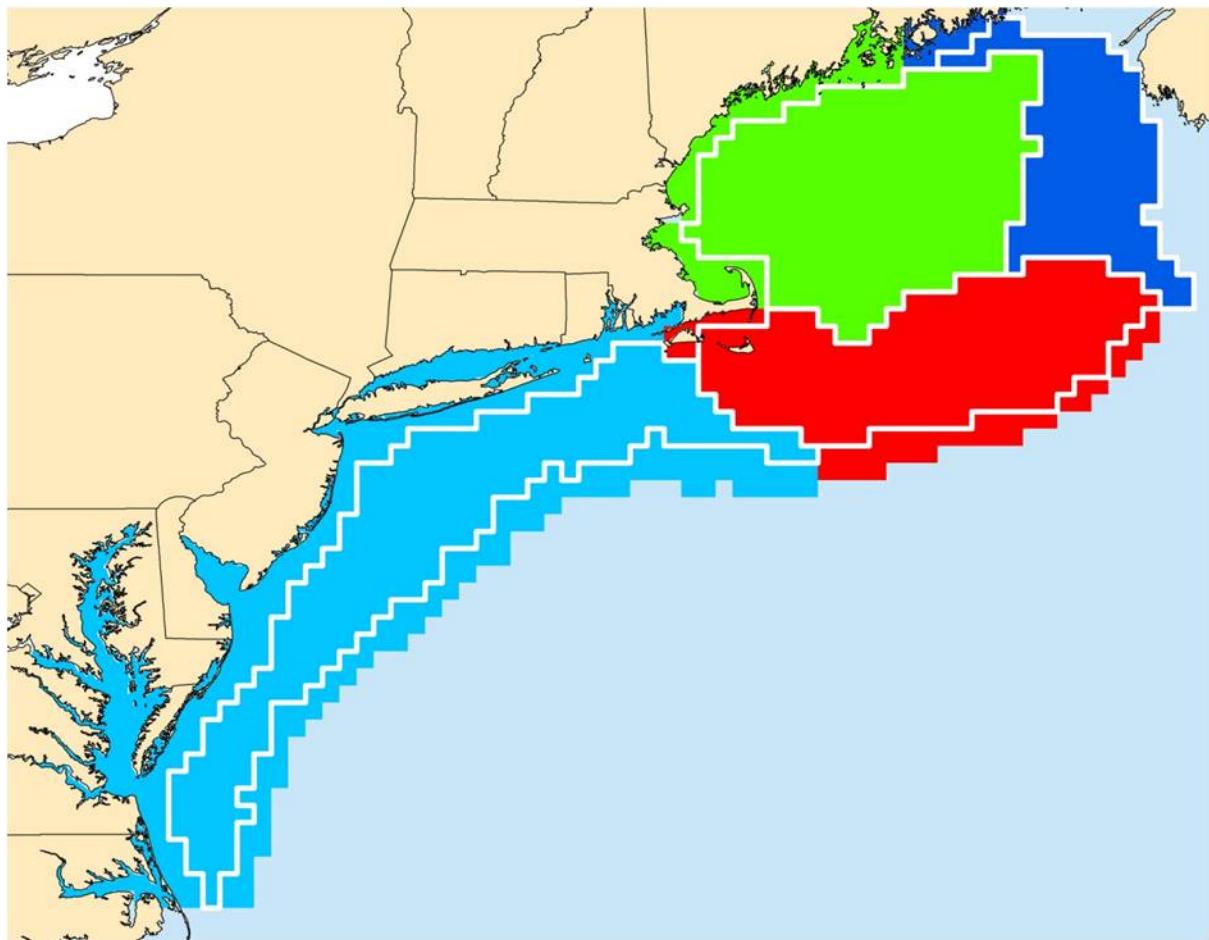


Figure 15.1: Map of the four Ecological Production Units, including the Mid-Atlantic Bight (light blue), Georges Bank (red), Western-Central Gulf of Maine (or Gulf of Maine; green), and Scotian Shelf-Eastern Gulf of Maine (dark blue)

Chapter 16

Forage Fish Energy Density

Description: Forage Engery Density indicators

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2020), State of the Ecosystem - Mid-Atlantic (2020)

Indicator category:

Contributor(s): Mark Wuenschel, Ken Oliveira and Kelcie Bean

Data steward: Mark Wuenschel mark.wuenschel@noaa.gov

Point of contact: Mark Wuenschel mark.wuenschel@noaa.gov

Public availability statement: Source data are publicly available.

16.1 Methods

A collaborative project between UMASS Dartmouth Biology Department (Dr. Ken Oliveira, M.S student Kelcie Bean) and NEFSC Population Biology Branch (Mark Wuenschel) is underway to evaluate energy content of forage species. The study focuses on the following species; Atlantic herring, alewife, silver hake, butterfish, northern sandlance, Atlantic mackerel, longfin squid, and northern shortfin squid. Samples have been analyzed for proximate composition and energy density from 2017 and 2018 NEFSC spring and fall bottom trawl surveys (Bean 2019, table below). Predictive relationships between the percent dry weight of samples and energy density were developed, and samples collected from 2019 surveys are currently being analyzed for percentage dry weight to enable estimation of energy content. The energy density of forage species differed from prior studies in the 1980s and 1990s (Steimle and Terranova (1985), Lawson, Magalhães, and Miller (1998)).

16.1.1 Data sources

2017 and 2018 NEFSC spring and fall bottom trawl surveys.

16.1.2 Data extraction

16.1.3 Data analysis

Sampling and laboratory analysis is ongoing, with the goal of continuing routine monitoring of energy density of these species.

Table 16.1: Forage fish energy content

Species	2017				2018				Total	
	Spring		Fall		Spring		Fall		Mean ED (SD)	N
	Mean ED (SD)	N	Mean ED (SD)	N	Mean ED (SD)	N	Mean ED (SD)	N		
Alewife	6.84 (1.62)	128	8.12 (1.46)	50	6.45 (1.21)	47	7.41 (1.6)	42	7.1 (1.62)	227
Atl. Herring	5.34 (0.94)	122	5.77 (1.31)	52	6.69 (0.85)	51	5.41 (1.34)	50	5.69 (1.19)	223
Atl. Mackerel		NA	7.24 (1.13)	50	5.33 (0.86)	51	6.89 (1.07)	50	6.48 (1.32)	151
Butterfish	7.13 (1.59)	65	7.31 (1.45)	89	4.91 (1.12)	53	8.1 (2.7)	50	6.92 (2.04)	204
Illex	5.54 (0.4)	77	5.43 (0.51)	52	5.5 (0.52)	50	4.76 (0.79)	50	5.33 (0.63)	201
Loligo	5.22 (0.36)	83	5.24 (0.26)	60	4.84 (0.63)	52	4.6 (0.72)	50	5.02 (0.56)	201
Sand lance	6.66 (0.54)	18		NA	5.78 (0.34)	60	7.99 (0.74)	8	6.17 (0.81)	100
Silver hake	4.25 (0.39)	189	4.42 (0.45)	50	4.19 (0.39)	50	4.55 (0.63)	50	4.31 (0.46)	339

16.1.4 Data processing

Code for building the table used in the SOE can be found [here](#).

Chapter 17

Gulf Stream Index

Description: Annual time series of the Gulf Stream index

Indicator category: Published method

Found in: State of the Ecosystem - New England (2019, 2020)

Contributor(s): Terry Joyce, Rong Zhang

Data steward: Vincent Saba, vincent.saba@noaa.gov

Point of contact: Vincent Saba, vincent.saba@noaa.gov

Public availability statement: Source data are publicly available

17.1 Methods

17.1.1 Data sources

Ocean temperature data from NOAA's National Centers for Environmental Information (NCEI) Ocean temperatures at 200 m are available at https://www.nodc.noaa.gov/OC5/3M_HEAT_CONTENT/.

17.1.2 Data analysis

Summarized from Joyce et al. (2019), ocean temperature data from NOAA's National Centers for Environmental Information (NCEI) were sorted by latitude, longitude, and time using a resolution of 1° of longitude, latitude, and 3 months of time, respectively, with a Gaussian squared weighting from the selected desired point in a window twice the size of the desired resolution. Editing was used to reject duplicate samples and 3σ outliers from each selected sample point prior to performing the weighting and averaging; the latter was only carried out when there were at least three data points in the selected interval for each sample point. Typically, 50 or more data values were available. The resulting temperature field was therefore smoothed. Data along the Gulf Stream north wall at nine data points were used to assemble a spatial/temporal sampling of the temperature at 200m data along the north wall from 75°W to 55°W. The leading mode of temperature variability of the Gulf Stream is equivalent to a north-south shift of 50–100 km, which is zonally of one sign and amounts to 50% of the seasonal-interannual variance between 75°W and 55°W. The temporal behavior of this mode (PC1) shows the temporal shift of the Gulf Stream path with a dominant approximately 8- to 10-year periodicity over much of the period.

For detailed analytical methods, see Joyce et al. (2019).

17.1.3 Data Processing

The Gulf Stream index data set was formatted for inclusion in the `ecodata` R package with the code found here.

17.1.4 Plotting

The plot below was built using the code found here.

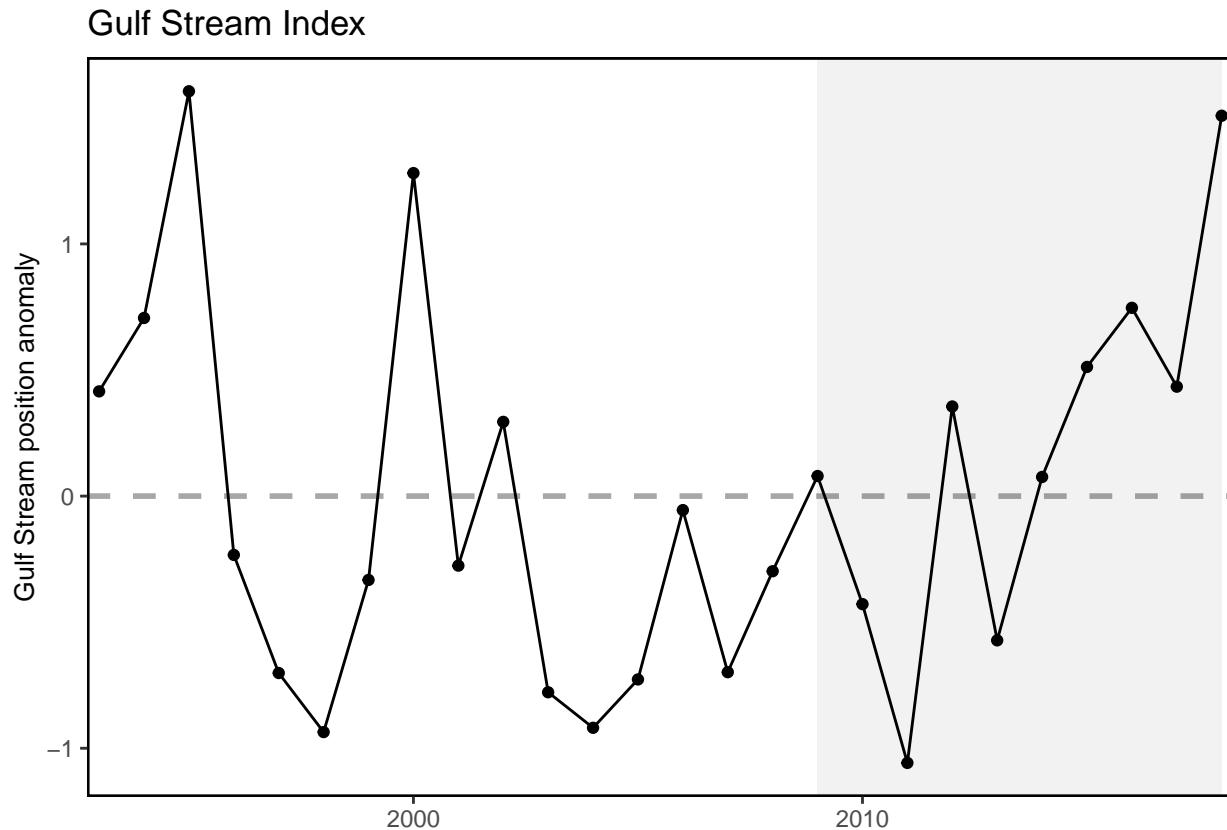


Figure 17.1: Gulf Stream Index

Chapter 18

Harbor Porpoise Bycatch

Description: Harbor Porpoise Indicator

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018, 2019), State of the Ecosystem - Mid-Atlantic (2018, 2019)

Indicator category: Synthesis of published information; Published methods

Contributor(s): Christopher D. Orphanides

Data steward: Chris Orphanides, chris.orphanides@noaa.gov

Point of contact: Chris Orphanides, chris.orphanides@noaa.gov

Public availability statement: Source data are available in public stock assessment reports (2018 report in-press). Derived data as shown in the 2018 SOE reports are available here

18.1 Methods

18.1.1 Data sources

Reported harbor porpoise bycatch estimates and potential biological removal levels can be found in publicly available documents; detailed here. The most recent bycatch estimates for 2016 were taken from the 2018 stock assessment (in-press). More detailed documentation as to the methods employed can be found in NOAA Fisheries Northeast Fisheries Science Center (NEFSC) Center Reference Documents (CRDs) found on the NEFSC publications page.

The document for the 2016 estimates (CRD 19-04) is available here. Additional methodological details are available for previous year's estimates and are documented in numerous published CRDs: CRD 17-18, CRD-16-05, CRD 15-15, CRD 14-02, CRD 13-13, CRD 11-08, CRD 10-10, CRD 07-20, CRD 06-13, CRD 03-18, CRD 01-15, and CRD 99-17.

18.1.2 Data extraction

Annual gillnet bycatch estimates are documented in a CRD (see sources above). These feed into the Stock Assessment Reports which report both the annual bycatch estimate and the mean 5-year estimate. The 5-year estimate is the one used for management purposes, so that is the one provided for the SOE plot.

18.1.3 Data analysis

Bycatch estimates as found in stock assessment reports were plotted along with confidence intervals. The confidence intervals were calculated from published CVs assuming a normal distribution ($\sigma = \mu CV$; $CI = \bar{x} \pm \sigma * 1.96$).

Data were analyzed and formatted for inclusion in the `ecodata` R package using the R code found [here](#).

18.1.4 Plotting

Code used to plot harbor porpoise data can be found [here](#).

Chapter 19

Highly Migratory Species Landings

Description: Highly Migratory Species Landings

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2020), State of the Ecosystem - Mid-Atlantic (2020)

Indicator category: Synthesis of published information, Database pull with analysis

Contributor(s): George Silva, Heather Baertlein, and Cliff Hutt

Data steward: Kimberly Bastille

Point of contact: George Silva george.silva@noaa.gov

Public availability statement: Source data are publicly available.

19.1 Methods

19.1.1 Data sources

Data from eDealer database (website) and Bluefin Tuna Dealer reports on SAFIS.

19.1.2 Data extraction

Data was processed for Fisheries of the United States and then aggregated by region to avoid confidentiality issues.

19.1.3 Data analysis

High migratory landings include 19 species of tunas, sharks and swordfish.

Data was analyzed using Excel pivot tables.

19.1.4 Data processing

HMS landings data were formatted for inclusion in the `ecodata` R package using the R code found here.

19.1.5 Plotting

The plot below was built using the code found here.

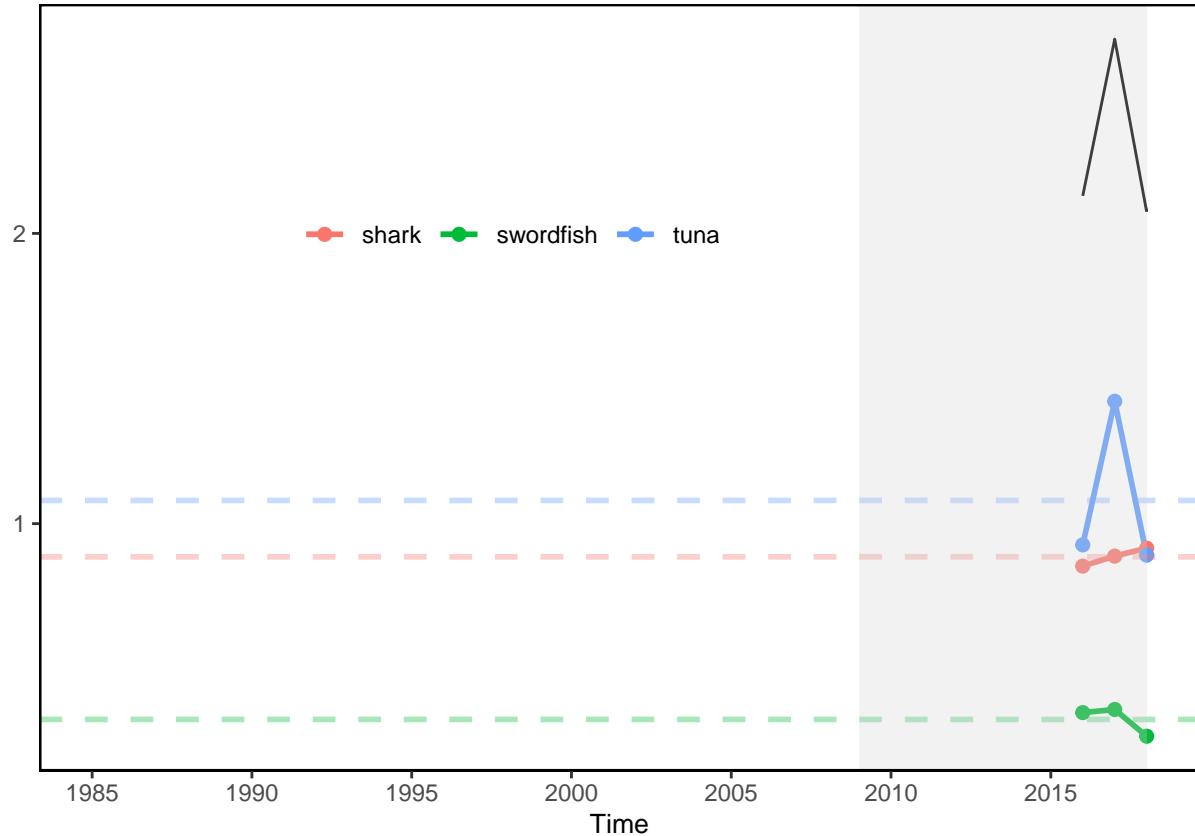


Figure 19.1: Highly migratory species landings from 2016-2018 grouped by sharks, tunas and swordfish.

Chapter 20

Ichthyoplankton Diversity

Description: NOAA NEFSC Oceans and Climate branch public ichthyoplankton dataset

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018, 2019), State of the Ecosystem - Mid-Atlantic (2018, 2019)

Indicator category: Database pull with analysis

Contributor(s): Harvey J. Walsh

Data steward: Harvey Walsh, harvey.walsh@noaa.gov

Point of contact: Harvey Walsh, harvey.walsh@noaa.gov

Public availability statement: Source data are available to the public here. Derived data for this indicator are available here.

20.1 Methods

Data from the NOAA Northeast Fisheries Science Center (NEFSC) Oceans and Climate branch (OCB) public dataset were used to examine changes in diversity of abundance among 45 ichthyoplankton taxa. The 45 taxa were established (Walsh et al. 2015), and include the most abundant taxa from the 1970s to present that represent consistency in the identification of larvae.

20.1.1 Data sources

Multi-species plankton surveys cover the entire Northeast US shelf from Cape Hatteras, North Carolina, to Cape Sable, Nova Scotia, four to six times per year. A random-stratified design based on the NEFSC bottom trawl survey design (Azarowitz 1981) is used to collect samples from 47 strata. The number of strata is lower than the trawl survey as many of the narrow inshore and shelf-break strata are combined in the EcoMon design. The area encompassed by each stratum determined the number of samples in each stratum. Samples were collected both day and night using a 61 cm bongo net. Net tow speed was 1.5 knots and maximum sample depth was 200 m. Double oblique tows were a minimum of 5 mintues in duration, and fished from the surface to within 5 m of the seabed or to a maximum depth of 200 m. The volume filtered of all collections was measured with mechanical flowmeters mounted across the mouth of each net.

Processing of most samples was conducted at the Morski Instytut Rybacki (MIR) in Szczecin, Poland; the remaining samples were processed at the NEFSC or the Atlantic Reference Center, St Andrews, Canada. Larvae were identified to the lowest possible taxa and enumerated for each sample. Taxon abundance for each station was standardized to number under 10 m^{-2} sea surface.

20.1.2 Data extraction

Data retrieved from NOAA NEFSC Oceans and Climate branch public dataset (Filename: "EcoMon_Plankton_Data_v3_0.xlsx". File Date: 10/20/2016).

20.1.3 Data analysis

All detailed data processing steps are not currently included in this document, but general steps are outlined. Data were grouped into seasons: spring = February, March, April and fall = September, October, November. Stratified weighted mean abundance was calculated for each taxon for each year and season across all plankton strata ($n = 47$) for 17 years (1999 to 2015). Shannon Diversity Index and count of positive taxon was calculated for each season and year.

MATLAB code used to calculate diversity indices:

20.1.4 Data processing

Ichthyoplankton diversity data sets were formatted for inclusion in the `ecodata` R package using the R code found here.

20.1.5 Plotting

Code used to plot ichthyoplankton diversity can be found [here](#).

Chapter 21

Inshore bottom trawl surveys

Description: Inshore surveys include the Northeast Area Monitoring and Assessment Program (NEAMAP) survey, Massachusetts Division of Marine Fisheries Bottom Trawl Survey, and Maine/New Hampshire Inshore Trawl Survey.

Indicator category: Database pull with analysis

Found in: State of the Ecosystem - Mid-Atlantic (2019,2020), State of the Ecosystem - New England (2019, 2020)

Contributor(s): James Gartland, Matt Camisa, Rebecca Peters, Sean Lucey

Data steward: Kimberly Bastille, kimberly.bastille@noaa.gov

Points of contact: James Gartland (NEAMAP), jgartlan@vims.edu; Rebecca Peters (ME/NH survey), rebecca.j.peters@maine.gov; Sean Lucey (MA Inshore Survey), sean.lucey@noaa.gov

Public availability statement: Data are available upon request.

21.1 Methods

21.1.1 Data Sources

All inshore bottom trawl survey data sets were derived from raw survey data. NEAMAP source data are available for download here. More detailed information describing NEAMAP survey methods is available on the NEAMAP website. ME/NH inshore survey data are available upon request (see Points of Contact). Technical documentation for ME/NH survey methods and survey updates are made available through the Maine Department of Marine Resources. Data from the MA Inshore Bottom Trawl Survey are stored on local servers at the Northeast Fisheries Science Center (Woods Hole, MA), and are also available upon request. More information about the MA Inshore Bottom Trawl Survey is available [here](#).

21.1.2 Data extraction

Source data from the Massachusetts DMF Bottom Trawl Survey were extracted using this R script.

21.1.3 Data Processing

The following R code was used to process inshore bottom trawl data into the `ecodata` R package.

New England

https://github.com/NOAA-EDAB/ecodata/blob/master/data-raw/get_inshore_survdat.R

Massachusetts https://github.com/NOAA-EDAB/ecodata/blob/master/data-raw/get_mass_inshore_survey.R

Mid-Atlantic (NEAMAP) https://github.com/NOAA-EDAB/ecodata/blob/master/data-raw/get_mab_inshore_survey.R

21.1.4 Data Analysis

Biomass indices were provided as stratified mean biomass (kg tow^{-1}) for all inshore surveys. Time series of stratified mean biomass were calculated for ME/NH and NEAMAP surveys through the following procedure:

1. All species catch weights were summed for each tow and for each feeding guild category.
2. The average weight per tow, associated variances and standard deviation for each survey, region, stratum, and feeding guild was calculated.
3. Stratified mean biomass was then calculated as the sum of the weighted averages of the strata, where the weight of a given stratum was the proportion of the survey area accounted for by that stratum.

Stratified mean biomass was also calculated for the MA Inshore Bottom Trawl Survey. These calculations followed those used to find stratified mean biomass by feeding guild in the NEFSC Bottom Trawl Survey and are described in greater detail there. The R code used to derive the stratified mean biomass indices for MA Inshore time series is provided below.

R code used for analysis can be found [here](#).

21.1.5 Plotting

21.1.5.1 NEAMAP

21.1.5.2 Massachusetts

21.1.5.3 Maine-New Hampshire

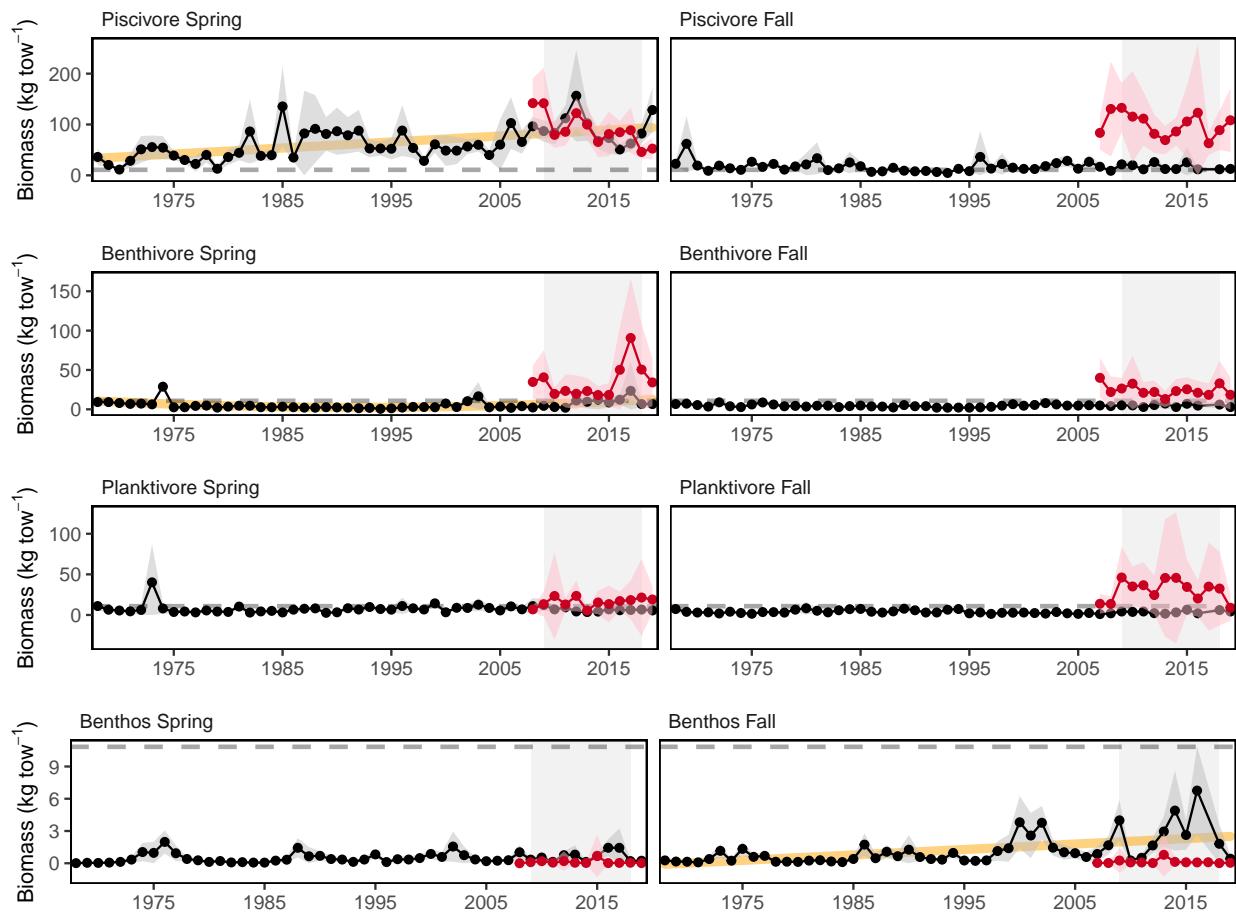


Figure 21.1: Spring (left) and fall (right) surveyed biomass in the Mid-Atlantic Bight. Data from the NEFSC Bottom Trawl Survey are shown in black, with NEAMAP shown in red.

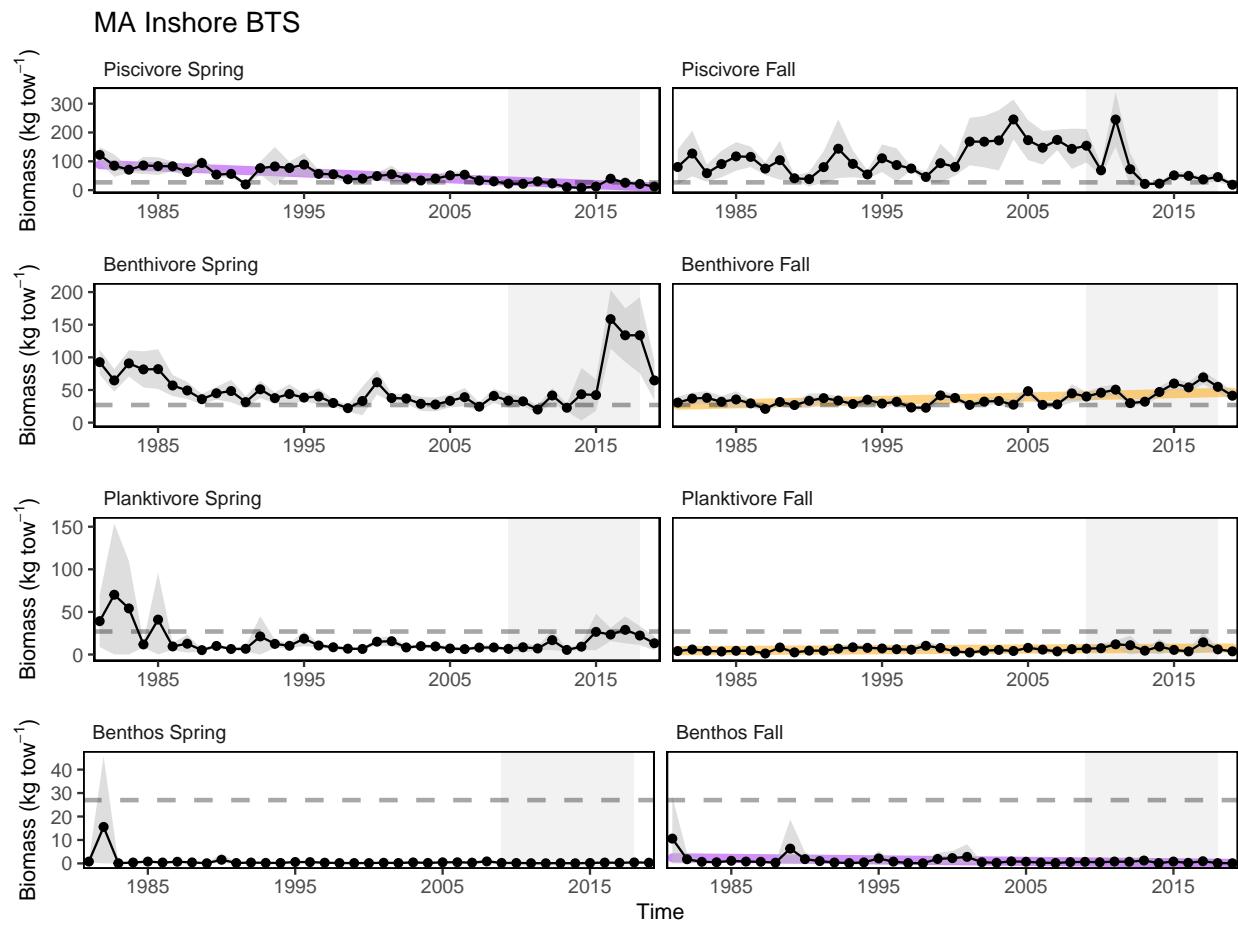


Figure 21.2: Spring (left) and fall (right) surveyed biomass from the MA state inshore bottom trawl survey.

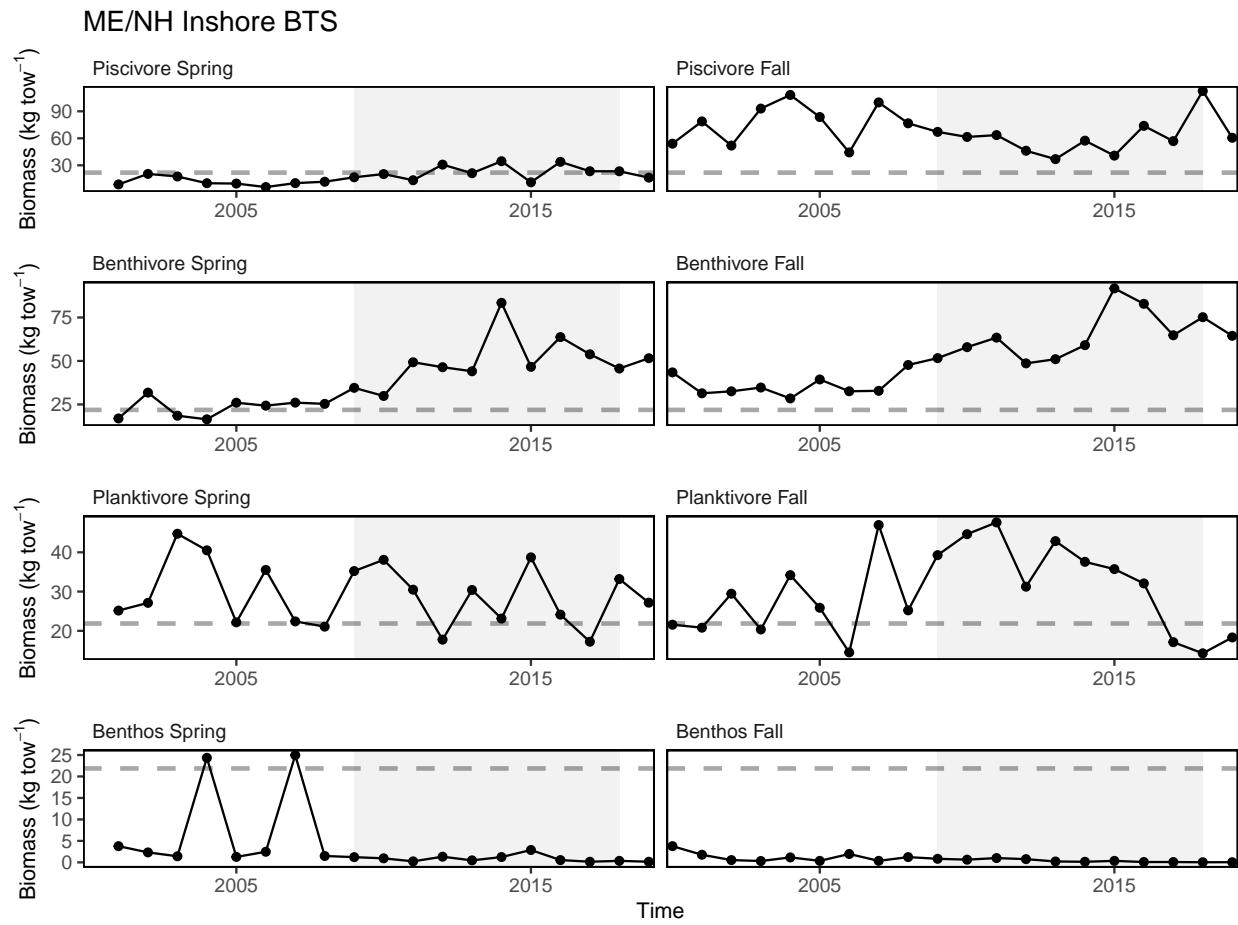


Figure 21.3: Spring (left) and fall(right) surveyed biomass from the ME/NH state inshore bottom trawl survey.

Chapter 22

Commercial Landings Data

Description: Commercial landings data pull

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2017, 2018, 2019,2020), State of the Ecosystem - Mid-Atlantic (2017, 2018, 2019,2020)

Indicator category: Database pull

Contributor(s): Sean Lucey

Data steward: Sean Lucey, Sean.Lucey@noaa.gov

Point of contact: Sean Lucey, Sean.Lucey@noaa.gov

Public availability statement: Raw data are not publically available due to confidentiality of individual fishery participants. Derived indicator outputs are available here.

22.1 Methods

Fisheries dependent data for the Northeast Shelf extend back several decades. Data from the 1960s on are housed in the Commercial database (CFDDB) of the Northeast Fisheries Science Center which contains the commercial fisheries dealer purchase records (weigh-outs) collected by National Marine Fisheries Service (NMFS) Statistical Reporting Specialists and state agencies from Maine to Virginia. The data format has changed slightly over the time series with three distinct time frames as noted in Table 22.1 below.

Comlands is an R database pull that consolidates the landings records from 1964 on and attempts to associate them with NAFO statistical areas (Figure 22.1). The script is divided into three sections. The first pulls domestic landings data from the yearly landings tables and merges them into a single data source. The second section applies an algorithm to associate landings that are not allocated to a statistical area using similar characteristics of the trip to trips with known areas. The final section pulls foreign landings from the

Table 22.1: Data formats

Table	Years
WOLANDS	1964 - 1981
WODETS	1982 - 1993
CFDETS_AA	> 1994

Table 22.2: Gear types used in commercial landings

Major gear	
1	Otter Trawls
2	Scallop Dredges
3	Other Dredges
4	Gillnets
5	Longlines
6	Seines
7	Pots/Traps
8	Midwater
9	Other

Northwest Atlantic Fisheries Organization website and rectifies species and gear codes so they can be merged along with domestic landings.

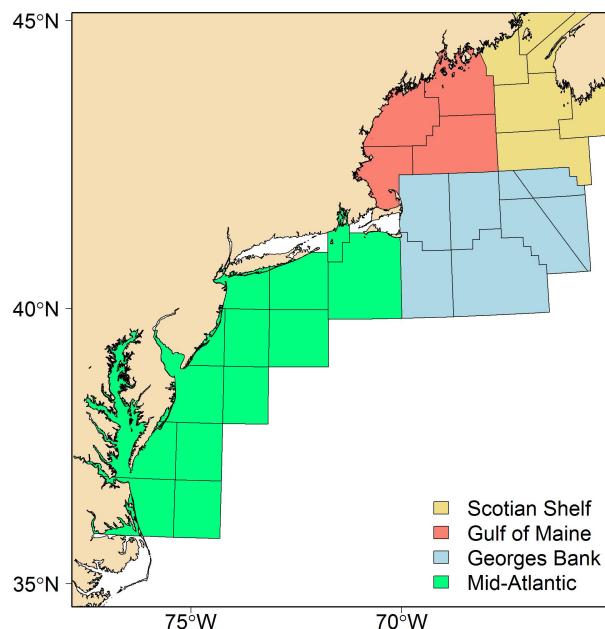


Figure 22.1: Map of the North Atlantic Fisheries Organization (NAFO) Statistical Areas. Colors represent the Ecological Production Unit (EPU) with which the statistical area is associated.

During the first section, the Comlands script pulls the temporal and spatial information as well as vessel and gear characteristics associated with the landings in addition to the weight, value, and utilization code of each species in the landings record. The script includes a toggle to use landed weights as opposed to live weights. For all but shellfish species, live weights are used for the State of the Ecosystem report. Due to the volume of data contained within each yearly landings table, landings are aggregated by species, utilization code, and area as well as by month, gear, and tonnage class. All weights are then converted from pounds to metric tons. Landings values are also adjusted for inflation using the Producer Price Index by Commodity for Processed Foods and Feeds: Unprocessed and Packaged Fish. Inflation is based on January of the terminal year of the data pull ensuring that all values are in current dollar prices.

Several species have additional steps after the data is pulled from CFDBS. Skates are typically landed as a species complex. In order to segregate the catch into species, the ratio of individual skate species in the NEFSC bottom trawl survey is used to disaggregate the landings. A similar algorithm is used to separate silver and offshore hake which can be mistaken for one another. Finally, Atlantic herring landings are pulled from a separate database as the most accurate weights are housed by the State of Maine. Comlands pulls from the State database and replaces the less accurate numbers from the federal database.

The majority of landings data are associated with a NAFO Statistical Area. For those that are not, Comlands attempts to assign them to an area using similar characteristics of trips where the area is known. To simplify this task, landings data are further aggregated into quarter and half year, small and large vessels, and eight major gear categories (Table 22.2). Landings are then proportioned to areas that meet similar characteristics based on the proportion of landings in each area by that temporal/vessel/gear combination. If a given attribute is unknown, the algorithm attempts to assign it one, once again based on matched characteristics of known trips. Statistical areas are then assigned to their respective Ecological Production Unit (Table 22.3).

Table 22.3: Statistical areas making up each EPU

EPU	Stat Areas
Gulf of Maine	500, 510, 512, 513, 514, 515
Georges Bank	521, 522, 523, 524, 525, 526, 551, 552, 561, 562
Mid-Atlantic	537, 539, 600, 612, 613, 614, 615, 616, 621, 622, 625, 626, 631, 632

The final step of Comlands is to pull the foreign landings from the NAFO database. US landings are removed from this extraction so as not to be double counted. NAFO codes and CFDBS codes differ so the script rectifies those codes to ensure that the data is seamlessly merged into the domestic landings. Foreign landings are flagged so that they can be removed if so desired.

22.1.1 Data sources

Comland is a database query of the NEFSC commercial fishery database (CFDBS). More information about the CFDBS is available [here](#).

22.1.2 Data extraction

R code used in the extraction process described above can be found [here](#).

22.1.2.1 Data Processing

The landings data were formatted for inclusion in the `ecodata` R package with this R code.

22.1.3 Data analysis

Fisheries dependent data from Comlands is used in several indicators for the State of the Ecosystem report; the more complicated analyses are detailed in their own sections. The most straightforward use of this data are the aggregate landings indicators. These are calculated by first assigning the various species into aggregate groups. Species are also marked by which management body manages them. Landings are then summed by year, EPU, aggregate group, and whether they are managed or not. Both managed and unmanaged totals are added together to get the final amount of total landings for that aggregate group within its respective region. Both the total and those landings managed by the management body receiving the report are reported. Proportions of managed landings to total landings are also reported in tabular form.

22.1.4 Plotting

The plot below was built using the code found here.

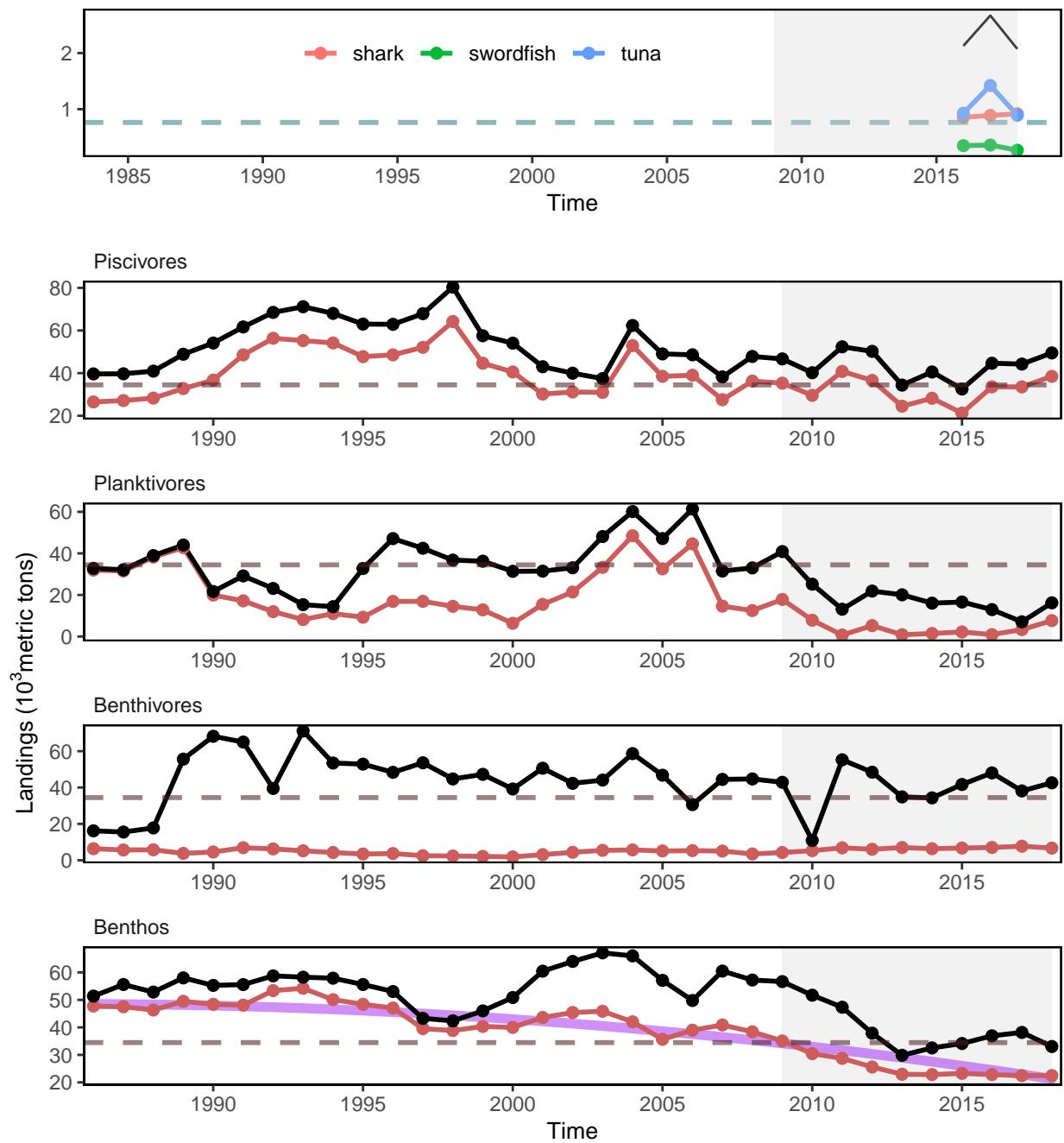


Figure 22.2: Mid-Atlantic commercial landings.

Chapter 23

Long-term Sea Surface Temperature

Description: Long-term sea-surface temperatures

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2017, 2018, 2019, 2020), State of the Ecosystem - Mid-Atlantic (2017, 2018, 2019, 2020)

Indicator category: Database pull

Contributor(s): Kevin Friedland

Data steward: Kevin Friedland, kevin.friedland@noaa.gov

Point of contact: Kevin Friedland, kevin.friedland@noaa.gov

Public availability statement: Source data are available here.

23.1 Methods

Data for long-term sea-surface temperatures were derived from the National Oceanographic and Atmospheric Administration (NOAA) extended reconstructed sea surface temperature data set (ERSST V5). The ERSST V5 dataset is parsed into $2^{\circ} \times 2^{\circ}$ gridded bins between 1854-present with monthly temporal resolution. Data were interpolated in regions with limited spatial coverage, and heavily damped during the period between 1854-1880 when collection was inconsistent (Huang, Thorne, et al. 2017a, 2017b). For this analysis, 19 bins were selected that encompassed the Northeast US Continental Shelf region (see Friedland and Hare 2007).

23.1.1 Data sources

This indicator is derived from the NOAA ERSST V5 dataset (Huang, Thorne, et al. 2017a).

23.1.2 Data extraction

R code used in extracting time series of long-term SST data can be found [here](#).

23.1.3 Data Processing

Data were formatted for inclusion in the `ecodata` R package with the R code found [here](#).

23.1.4 Plotting

The plot below was built using the code found [here](#).

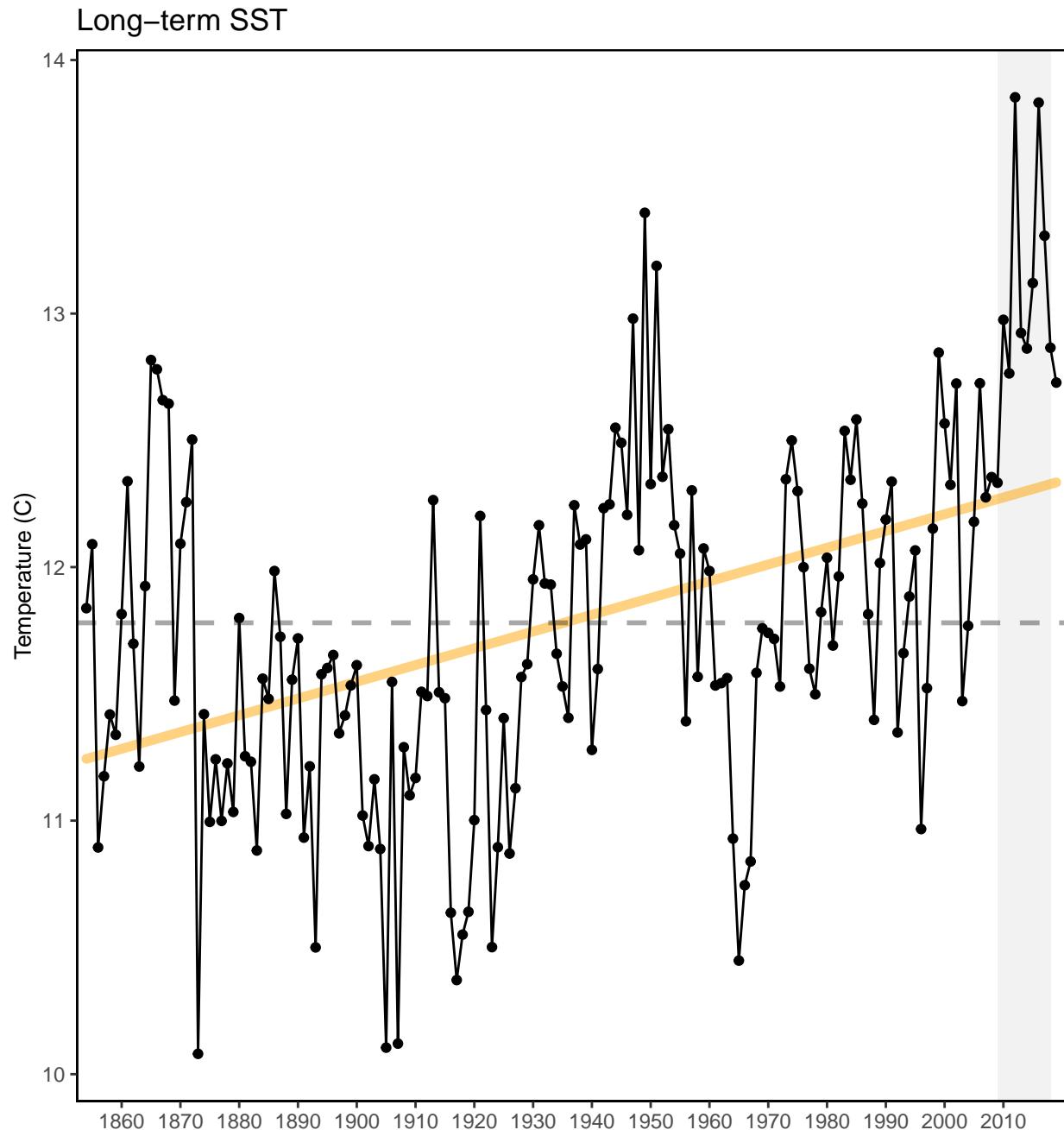


Figure 23.1: Long-term sea surface temperatures on the Northeast Continental Shelf.

Table 23.1: Coordinates used in NOAA ERSST V5 data extraction.

Longitude	Latitude
-74	40
-74	38
-72	40
-70	44
-70	42
-70	40
-68	44
-68	42

Chapter 24

Mid-Atlantic Harmful Algal Bloom Indicator

Description: An aggregation of reported algal bloom data in Chesapeake Bay between 2007-2017.

Found in: State of the Ecosystem - Mid-Atlantic (2018)

Indicator category: Database pull

Contributor(s): Sean Hardison, Virginia Department of Health

Data steward: Kimberly Bastille, kimberly.bastille@noaa.gov

Point of contact: Kimberly Bastille, kimberly.bastille@noaa.gov

Public availability statement: Source data for this indicator are available here. Processed time series can be found [here](#).

24.1 Methods

We presented two indicator time series for reports of algal blooms in the southern portion of Chesapeake Bay between 2007-2017. The first indicator was observations of algal blooms above 5000 cell ml⁻¹. This threshold was developed by the Virginia Department of Health (VDH) for *Microcystis* spp. algal blooms based on World Health Organization guidelines (Organization 2003; Health 2011). VDH also uses this same threshold for other algal species blooms in Virginia waters. When cell concentrations are above 5000 cell ml⁻¹, VDH recommends initiation of biweekly water sampling and that relevant local agencies be notified of the elevated cell concentrations.

The second indicator we reported, blooms of *Cochlodinium polykrikoides* at cell concentrations >300 cell ml⁻¹, was chosen due to reports of high ichthyotoxicity seen at these levels. Tang and Gobler (2009) showed that fish exposed to cultured *C. polykrikoides* at densities as low 330 cells ml⁻¹ saw 100% mortality within 1 hour, which is often far less than *C. polykrikoides* cell concentrations seen in the field. Algal bloom data were not available for 2015 nor 2010. The algal bloom information presented here are a synthesis of reported events, and has been updated to include data not presented in the 2018 State of the Ecosystem Report.

24.1.1 Data sources

Source data were obtained from VDH. Sampling, identification, and bloom characterization was completed by the VDH, Phytoplankton Analysis Laboratory at Old Dominion University (ODU), Reece Lab at the

Virginia Institute of Marine Science (VIMS), and Virginia Department of Environmental Quality. Problem algal species were targeted for identification via light microscopy followed by standard or quantitative PCR assays and/or enzyme-linked immunosorbent assay (ELISA). Reports specifying full methodologies from ODU, VIMS, and VDH source data are available upon request.

24.1.2 Data extraction

Data were extracted from a series of spreadsheets provided by the VDH. We quantified the number of algal blooms in each year reaching target cell density thresholds in the southern Chesapeake Bay.

R code used in extracting harmful algal bloom data can be found [here](#).

24.1.3 Data analysis

No data analysis steps took place for this indicator.

Chapter 25

New England Harmful Algal Bloom Indicator

Description: Regional incidence of shellfish bed closures due to presence of toxins associated with harmful algae.

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018)

Indicator Category: Synthesis of published information

Contributor(s): Dave Kulis, Donald M Anderson, Sean Hardison

Data steward: Kimberly Bastille, kimberly.bastille@noaa.gov

Point of contact: Kimberly Bastille, kimberly.bastille@noaa.gov

Public availability statement: Data are publicly available (see Data Sources below).

25.1 Methods

The New England Harmful Algal Bloom (HAB) indicator is a synthesis of shellfish bed closures related to the presence of HAB-associated toxins above threshold levels from 2007-2016 (Figure ??). Standard detection methods were used to identify the presence of toxins associated with Amnesic Shellfish Poisoning (ASP), Paralytic Shellfish Poisoning (PSP), and Diarrhetic Shellfish Poisoning (DSP) by state and federal laboratories.

25.1.0.1 Paralytic Shellfish Poisoning

The most common cause of shellfish bed closures in New England is the presence of paralytic shellfish toxins (PSTs) produced by the dinoflagellate *Alexandrium catenella*. All New England states except Maine relied on the Association of Official Analytical Chemists (AOAC) approved mouse bioassay method to detect PSTs in shellfish during the 2007-2016 period reported here (International 2005).

In Maine, PST detection methods were updated in May 2014 when the state adopted the hydrophilic interaction liquid chromatography (HILIC) UPLC-MS/MS protocol (Boundy et al. 2015) in concordance with National Shellfish Sanitation Program (NSSP) requirements. Prior to this, the primary method used to detect PST in Maine was with the mouse bioassay.

Table 25.1: Shellfish closure information providers.

State	Source Organization
Maine	Maine Department of Marine Resources
New Hampshire	New Hampshire Department of Environmental Services
Massachusetts	Massachusetts Division of Marine Fisheries
Rhode Island	Rhode Island Department of Environmental Management
Connecticut	Connecticut Department of Agriculture

25.1.0.2 Amnesic Shellfish Poisoning

Amnesic shellfish poisoning (ASP) is caused by the toxin domoic acid (DA), which is produced by several phytoplankton species belonging to the genus *Pseudo-nitzchia*. In New England, a UV-HPLC method (Quilliam, Xie, and Hardstaff 1995), which specifies a HPLC-UV protocol, is used for ASP detection.

25.1.0.3 Diarrhetic Shellfish Poisoning

Diarrhetic Shellfish Poisoning (DSP) is rare in New England waters, but the presence of the DSP-associated okadaic acid (OA) in mussels was confirmed in Massachusetts in 2015 (J. Deeds, personal communication, July 7, 2018). Preliminary testing for OA in Massachusetts utilized the commercially available Protein Phosphatase Inhibition Assay (PPIA) and these results are confirmed through LC-MS/MS when necessary (Smienk et al. 2012; Stutts and Deeds 2017).

25.1.1 Data sources

Data used in this indicator were drawn from the 2017 Report on the ICES-IOC Working Group on Harmful Algal Bloom Dynamics (WGHABD). The report and data are available [here](#).

Closure information was collated from information provided by the following organizations:

25.1.2 Data extraction

Data were extracted from the original report visually and accuracy confirmed with report authors.

25.1.3 Data analysis

No data analysis steps took place for this indicator.

25.1.4 Plotting

The script used to develop the figure in the SOE report can be found [here](#).

Chapter 26

Marine Heatwave

Description: Marine Heatwave

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2020), Mid-Atlantic (2020)

Indicator category: Published methods, Database pull with analysis

Contributor(s): Vincent Saba

Data steward: Kimberly Bastille kimberly.bastille@noaa.gov

Point of contact: Vincent Saba vincent.saba@noaa.gov

Public availability statement:

26.1 Methods

Marine heatwave analysis for Georges Bank, Gulf of Maine, and the Middle Atlantic Bight according to the definition in Hobday et al. (2016).

26.1.1 Data sources

NOAA high-res OISST (daily, 25-km, 1982-2019) https://www.esrl.noaa.gov/psd/cgi-bin/db_search/DBListFiles.pl?did=132&tid=79458&vid=2423

26.1.2 Data extraction

Each yearly file (global) was downloaded, concatenated into a single netcdf file using nco (Unix), and then cropped to the USNES region using Ferret. Each EPU's time-series of SST was averaged using .shp file boundaries for the MAB, GB, and GOM (also done in Ferret) and saved to the three .csv files.

26.1.3 Data analysis

The marine heatwave metrics Maximum Intensity [deg. C] and Cumulative Intensity [deg. C x days] are calculated using NOAA OISST daily sea surface temperature data (25-km resolution) from January 1982 to December 2019. The heatwaves are calculated based on the algorithms in Hobday et al. 2016 and by using a climatology of 1982-2010. These metrics were run R using <https://robschlegel.github.io/heatwaveR/>

26.1.4 Data processing

Marine Heatwave data were formatted for inclusion in the `ecodata` R package using this R code.

26.1.5 Plotting

Code used for the plots below can be found [here](#).

Mid-Atlantic Marine Heatwave Intensity

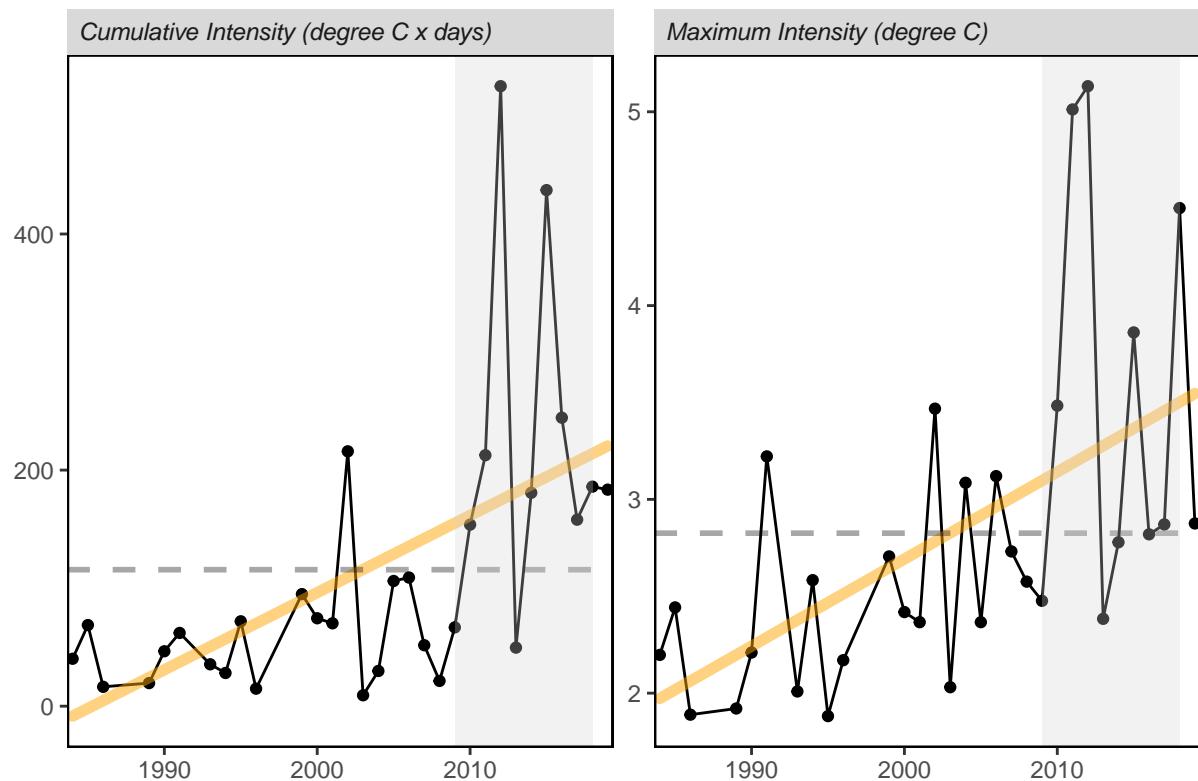


Figure 26.1: Cumulative and maximum marine heatwave in the Mid-Atlantic

Chapter 27

Verified Records of Southern Kingfish

Description: Fisheries Observer Data – Verified Records of Southern Kingfish

Found in: State of the Ecosystem - Mid-Atlantic (2018)

Indicator category: Database pull

Contributor(s): Debra Duarte, Loren Kellogg

Data steward: Gina Shield, gina.shield@noaa.gov

Point of contact: Gina Shield, gina.shield@noaa.gov

Public availability statement: Due to PII concerns data for this indicator are not publicly available.

27.1 Methods

27.1.1 Data sources

The Fisheries Sampling Branch deploys observers on commercial fisheries trips from Maine to North Carolina. On observed tows, observers must fully document all kept and discarded species encountered. Observers must comply with a Species Verification Program (SVP), which requires photo or sample submissions of high priority species at least once per quarter. Photos and samples submitted for verification are identified independently by at least two reviewers.

The derived data presented in the Mid-Atlantic State of the Ecosystem report for southern kingfish include records verified by the SVP program only. The occurrence of southern kingfish in SVP records were chosen for inclusion in the report due to the recent increases of the species in SVP observer records since 2010. These data are not a complete list from the New England Fisheries Observer Program (NEFOP). Southern Kingfish are less common than Northern Kingfish in observer data and are possibly misidentified so we have initially included records here only when a specimen record was submitted to and verified through the SVP (see Data extraction).

27.1.2 Data extraction

SQL query for observer data extraction can be found [here](#).

27.1.3 Data analysis

Time series were summed by year and plotted, and mapped data for individual records were plotted according to the location where gear was hauled. As coordinate data were not always available for each record, the map does not include all occurrences of southern kingfish, but was included for spatial context.

27.1.4 Plotting

Code used to produce the plot below can be found [here](#).

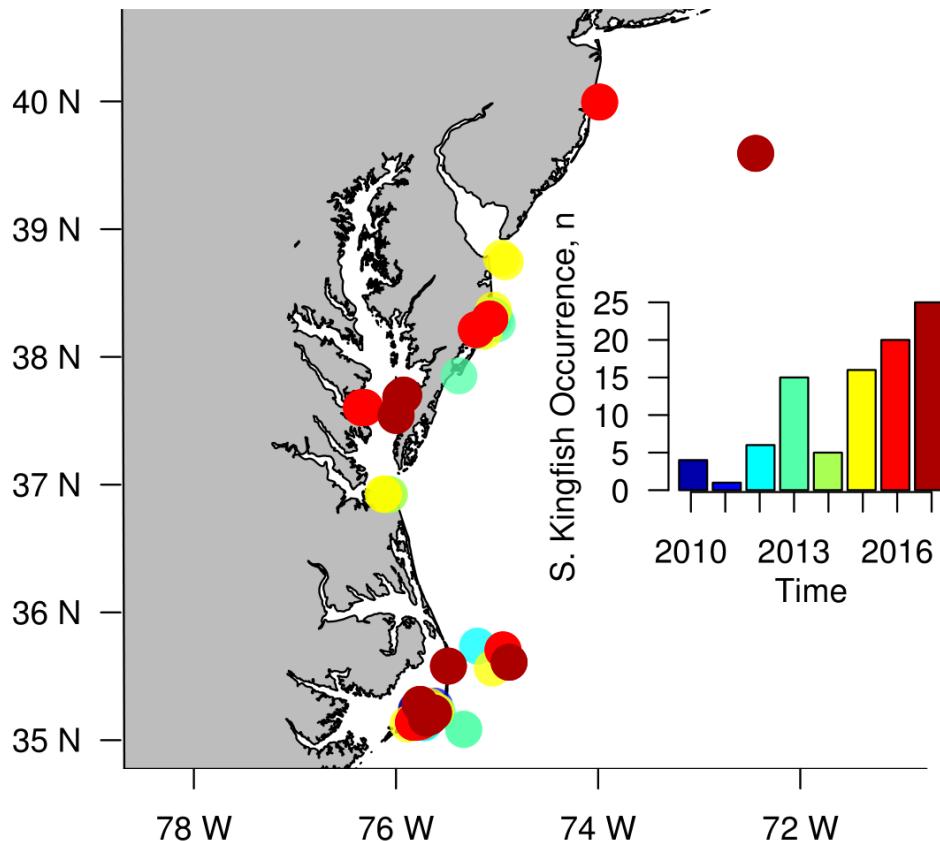


Figure 27.1: Verified records of Southern Kingfish occurrence in the Mid-Atlantic.

Chapter 28

Habitat Occupancy Models

Description: Habitat Occupancy

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018), State of the Ecosystem - Mid-Atlantic (2018)

Indicator category: Database pull with analysis; Extensive analysis; not yet published; Published methods

Contributor(s): Kevin Friedland

Data steward: Kevin Friedland, kevin.friedland@noaa.gov

Point of contact: Kevin Friedland, kevin.friedland@noaa.gov

Public availability statement: Source data are available upon request (see Survdat, CHL/PP, and Data Sources below for more information). Model-derived time series are available here.

28.1 Methods

Habitat area with a probability of occupancy greater than 0.5 was modeled for many species throughout the Northeast Large Marine Ecosystem (NE-LME) using random forest decision tree models.

28.1.1 Data sources

Models were parameterized using a suite of static and dynamic predictor variables, with occurrence and catch per unit effort (CPUE) of species from spring and fall Northeast Fisheries Science Center (NEFSC) bottom trawl surveys (BTS) serving as response variables. Sources of variables used in the analyses are described below.

28.1.1.1 Station depth

The NEFSC BTS data included depth observations made concurrently with trawls at each station. Station depth was a static variable for these analyses.

28.1.1.2 Ocean temperature and salinity

Sea surface and bottom water temperature and salinity measurements were included as dynamic predictor variables in the model, and were collected using Conductivity/Temperature/Depth (CTD) instruments. Ocean temperature and salinity measurements had the highest temporal coverage during the spring (February-April) and fall (September-November) months. Station salinity data were available between 1992-2016.

28.1.1.3 Habitat descriptors

A variety of benthic habitat descriptors were incorporated as predictor variables in occupancy models (Table 28.1). The majority of these parameters are based on depth (e.g. *BPI*, *VRM*, *Prcury*, *rugosity*, *seabedforms*, *slp*, and *slpslp*). The vorticity variable is based on current estimates, and the variable *soft_sed* based on sediment grain size.

Table 28.1: Habitat descriptors used in model parameterization.

Variables	Notes
Namera_vrm	Vector Ruggedness Measure (VRM) measures terrain ruggedness as the variation in three-dimensional orientation of grid cells with
Prcurv (2 km, 10 km, and 20 km)	Benthic profile curvature at 2km, 10km and 20 km spatial scales was derived from depth data.
Rugosity	A measure of small-scale variations of amplitude in the height of a surface, the ratio of the real to the geometric surface area.
seabedforms	Seabed topography as measured by a combination of seabed position and slope.
Slp (2 km, 10 km, and 20 km)	Benthic slope at 2km, 10km and 20km spatial scales.
Slpslp (2 km, 10 km, and 20 km)	Benthic slope of slope at 2km, 10km and 20km spatial scales
soft_sed	Soft-sediments is based on grain size distribution from the USGS usSeabed: Atlantic coast offshore surficial sediment data.
Vort (fall - fa; spring - sp; summer - su; winter - wi)	Benthic current vorticity at a 1/6 degree (approx. 19 km) spatial scale.

28.1.1.4 Zooplankton

Zooplankton data are acquired through the NEFSC Ecosystem Monitoring Program (“EcoMon”). For more information regarding the collection process for these data, see Kane (2007), Kane (2011), and Morse et al. (2017). The bio-volume of the 18 most abundant zooplankton taxa were considered as potential predictor variables.

28.1.1.5 Remote sensing data

Both chlorophyll concentration and sea surface temperature (SST) from remote sensing sources were incorporated as static predictor variables in the model. During the period of 1997-2016, chlorophyll concentrations were derived from observations made by the Sea-viewing Wide Field of View Sensor (SeaWiFS), Moderate Resolution Imaging Spectroradiometer (MODIS-Aqua), Medium Resolution Imaging Spectrometer (MERIS), and Visible and Infrared Imaging/Radiometer Suite (VIIRS).

28.1.2 Data processing

28.1.2.1 Zooplankton

Missing values in the EcoMon time series were addressed by summing data over five-year time steps for each seasonal time frame and interpolating a complete field using ordinary kriging. Missing values necessitated interpolation for spring data in 1989, 1990, 1991, and 1994. The same was true of the fall data for 1989, 1990, and 1992.

28.1.2.2 Remote sensing data

An overlapping time series of observations from the four sensors listed above was created using a bio-optical model inversion algorithm (Maritorena et al. 2010). Monthly SST data were derived from MODIS-Terra sensor data (available [here](#)).

28.1.2.3 Ocean temperature and salinity

Date of collection corrections for ocean temperature data were developed using linear regressions for the spring and fall time frames; standardizing to collection dates of April 3 and October 11 for spring and fall. No correction was performed for salinity data. Annual data for ocean temperature and salinity were combined with climatology by season through an optimal interpolation approach. Specifically, mean bottom temperature or salinity was calculated by year and season on a 0.5° grid across the ecosystem, and data from grid cells with >80% temporal coverage were used to calculate a final seasonal mean. Annual seasonal means were then used to calculate combined anomalies for seasonal surface and bottom climatologies.

An annual field was then estimated using raw data observations for a year, season, and depth using universal kriging (Hiemstra et al. 2008), with depth included as a covariate (on a standard 0.1° grid). This field was then combined with the climatology anomaly field and adjusted by the annual mean using the variance field from kriging as the basis for a weighted mean between the two. The variance field was divided into quartiles with the lowest quartile assigned a weighting of 4:1 between the annual and climatology values. The optimally interpolated field at these locations was therefore skewed towards the annual data, reflecting their proximity to actual data locations and associated low kriging variance. The highest kriging variance quartile (1:1) reflected less information from the annual field and more from the climatology.

28.1.3 Data analysis

28.1.3.1 Occupancy models

Prior to fitting the occupancy models, predictor variables were tested for multi-collinearity and removed if found to be correlated. The final model variables were then chosen utilizing a model selection process as

shown by Murphy, Evans, and Storfer (2010) and implemented with the R package **rfUtilities** (Evans and Murphy 2018). Occupancy models were then fit as two-factor classification models (absence as 0 and presence as 1) using the **randomForest** R package (Liaw and Wiener 2002).

28.1.3.2 Selection criteria and variable importance

The **irr** R package (Gamer, Lemon, and Singh 2012) was used to calculate Area Under the ROC Curve (AUC) and Cohen's Kappa for assessing accuracy of occupancy habitat models. Variable importance was assessed by plotting the occurrence of a variable as a root variable versus the mean minimum node depth for the variable (Paluszynska and Biecek 2017), as well as by plotting the Gini index decrease versus accuracy decrease.

28.1.4 Plotting

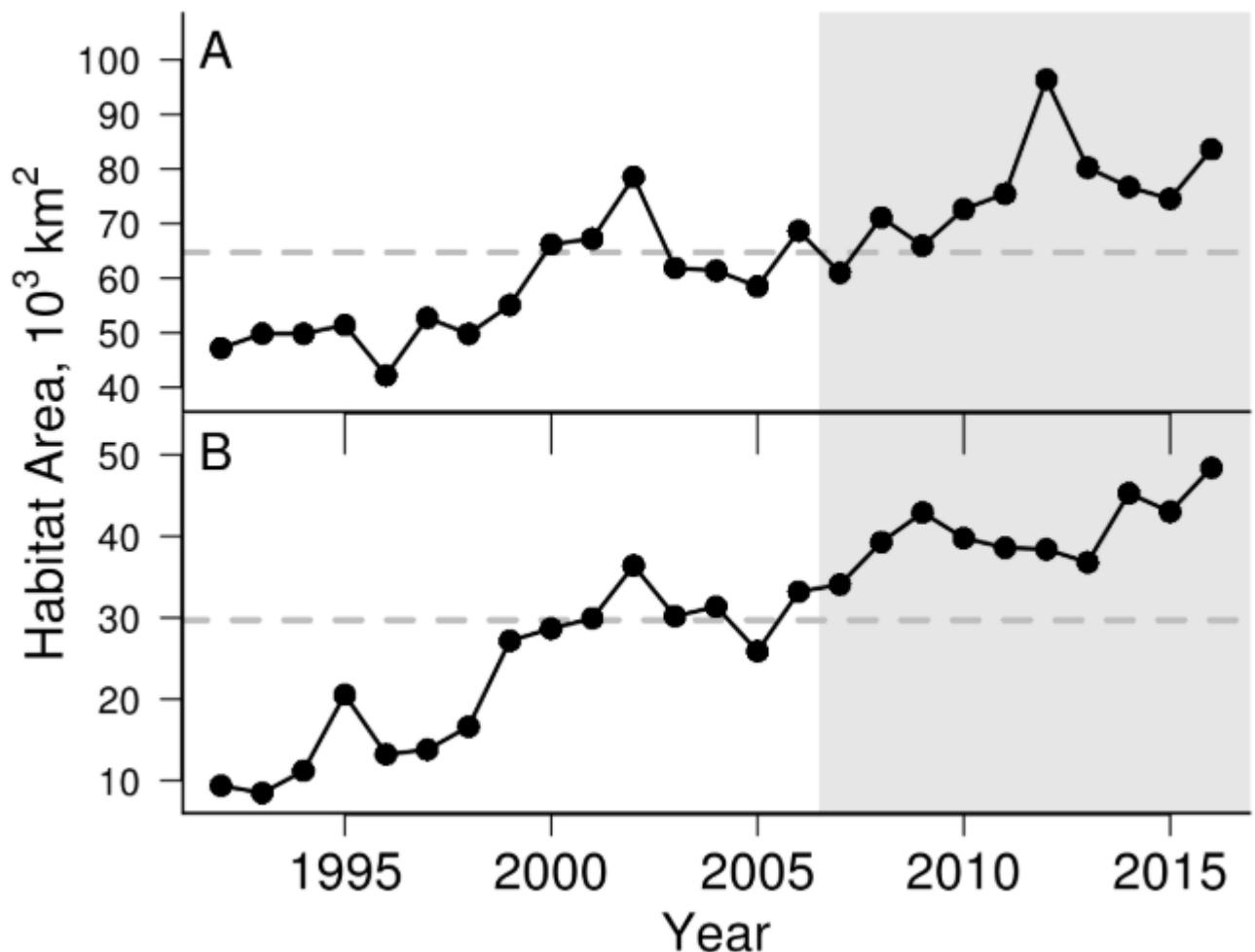


Figure 28.1: Summer flounder spring (A) and fall (B) occupancy habitat area in the Northeast Large Marine Ecosystem.

Chapter 29

Primary Production Required

Description: Time Series of Primary Production Required to sustain reported landings.

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2020+), State of the Ecosystem - Mid-Atlantic (2020+)

Indicator category: Database pull with analysis; Published methods

Contributor(s): Michael Fogarty, Andrew Beet

Data steward: Andrew Beet, andrew.beet@noaa.gov

Point of contact: Andrew Beet, andrew.beet@noaa.gov

Public availability statement: Source data is not publicly available due to PII restrictions.

29.1 Methods

The index is a measure of the impact of fishing on the base of the foodweb. The amount of potential yield we can expect from a marine ecosystem depends on the amount of production entering at the base of the food web, primarily in the form of phytoplankton; the pathways this energy follows to reach harvested species; the efficiency of transfer of energy at each step in the food web; and the fraction of this production that is removed by the fisheries. Species such as scallops and clams primarily feed directly on larger phytoplankton species and therefore require only one step in the transfer of energy. The loss of energy at each step can exceed 80-90%. For many fish species, as many as 2-4 steps may be necessary. Given the trophic level and the efficiency of energy transfer of the species in the ecosystem the amount phytoplankton production required (PPR) to account for the observed catch can be estimated.

The index for Primary Production Required (PPR) was adapted from (Pauly and Christensen 1995).

$$PPR_t = \sum_{i=1}^{n_t} \left(\frac{landings_{t,i}}{9} \right) \left(\frac{1}{TE} \right)^{TL_i - 1}$$

where n_t = number of species in time t , $landings_{t,i}$ = landings of species i in time t , TL_i is the trophic level of species i , TE = Trophic efficiency. The PPR estimate assumes a 9:1 ratio for the conversion of wet weight to carbon and a 15% transfer efficiency per trophic level, ($TE = 0.15$)

The index is presented as a percentage of estimated primary production (PP) available over the geographic region of interest, termed an Ecological Production Unit (EPU). The scaled index is estimated by dividing the PPR index in year t by the estimated primary production in time t .

$$scaledPPR_t = \frac{PPR_t}{PP_t}$$

The species selected in each year were determined by their cumulative contribution to total landings. A threshold of at least 80% of the total landings is used.

29.1.1 Data sources

Data for this index come from a variety of sources. The landings data come from the Commercial Fishery Database (CFDBS), species trophic level information come from fishbase and sealifebase, and primary production estimates are derived from satellites. Some of these data are typically not available to the public.

29.1.2 Data extraction

Landings are extracted from the commercial fisheries database (CFDBS) using the methods described in the chapter Commercial Landings Data.

Trophic level information for each species is obtained from fishbase and sealifebase using the R package rfishbase (Froese and Pauly 2019) in tandem with the package indexPPR.

Primary Production is estimated using the methods described in the chapter Chlorophyll a and Primary Production.

29.1.3 Data analysis

Annual (wet weight) landings are calculated for each species for a given EPU. For each year the landings are sorted in descending order by species and the cumulative landings are calculated. The top species that accounted for 80% of total cumulative landings are selected. The trophic level for each of these species are then obtained from fishbase/sealifebase. At this point the PPR index is calculated. The units of the index are $gCyear^{-1}$ for the EPU. The index is converted to $gCm^{-2}year^{-1}$ by dividing by the area (in m^2) of the EPU.

To normalize the index the total Primary Production for the given EPU is required. This is calculated as described in the chapter Chlorophyll a and Primary Production. The units are also converted to $gCm^{-2}year^{-1}$.

The index is then normalized by dividing the index in year t by the total primary production in time t .

29.1.4 Plotting

Four plots are produced for each EPU:

- The normalized PPR index (along with the associated landings).
- Total primary production
- Mean trophic level of the species included in the index (weighted by their landings)
- Species composition of landings

All created using the indexPPR

See the workedExample vignette in the indexPPR package for plotting code.

29.1.4.1 Georges Bank (GB)

29.1.4.2 Gulf of Maine (GOM)

29.1.4.3 Mid-Atlantic Bight (MAB)

Chapter 30

Fish Productivity Indicator

Description: Groundfish productivity estimated as the ratio of small fish to large fish

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2017, 2018, 2020), State of the Ecosystem - Mid-Atlantic (2017, 2018, 2019, 2020)

Indicator category: Database pull with analysis; Published methods

Contributor(s): Charles Perretti

Data steward: Charles Perretti, charles.perretti@noaa.gov

Point of contact: Charles Perretti, charles.perretti@noaa.gov

Public availability statement: Source data are available upon request.

30.1 Methods

30.1.1 Data sources

Survey data from the Northeast Fisheries Science Center (NEFSC) trawl database. These data in their derived form are available through Survdat.

30.1.2 Data extraction

Data were extracted from Survdat.

30.1.3 Data analysis

We defined size thresholds separating small and large fish for each species based on the 20th percentile of the length distribution across all years. This threshold was then used to calculate a small and large fish index (numbers below and above the threshold, respectively) each year. Although the length percentile corresponding to age-1 fish will vary with species, we use the 20th percentile as an approximation. Biomass was calculated using length-weight relationships directly from the survey data. Following Wigley, McBride, and McHugh (2003), the length-weight relationship was modeled as

$$\ln W = \ln a + b \ln L$$

where W is weight (kg), L is length (cm), and a and b are parameters fit via linear regression. The ratio of small fish numbers of the following year to larger fish biomass in the current year was used as the index of

recruitment success. The fall and spring recruitment success anomalies were averaged to provide an annual index of recruitment success.

Further details of methods described in Perretti et al. (2017a).

30.1.4 Data processing

Productivity data were formatted for inclusion in the `ecodata` R package using the R code found here.

30.1.5 Plotting

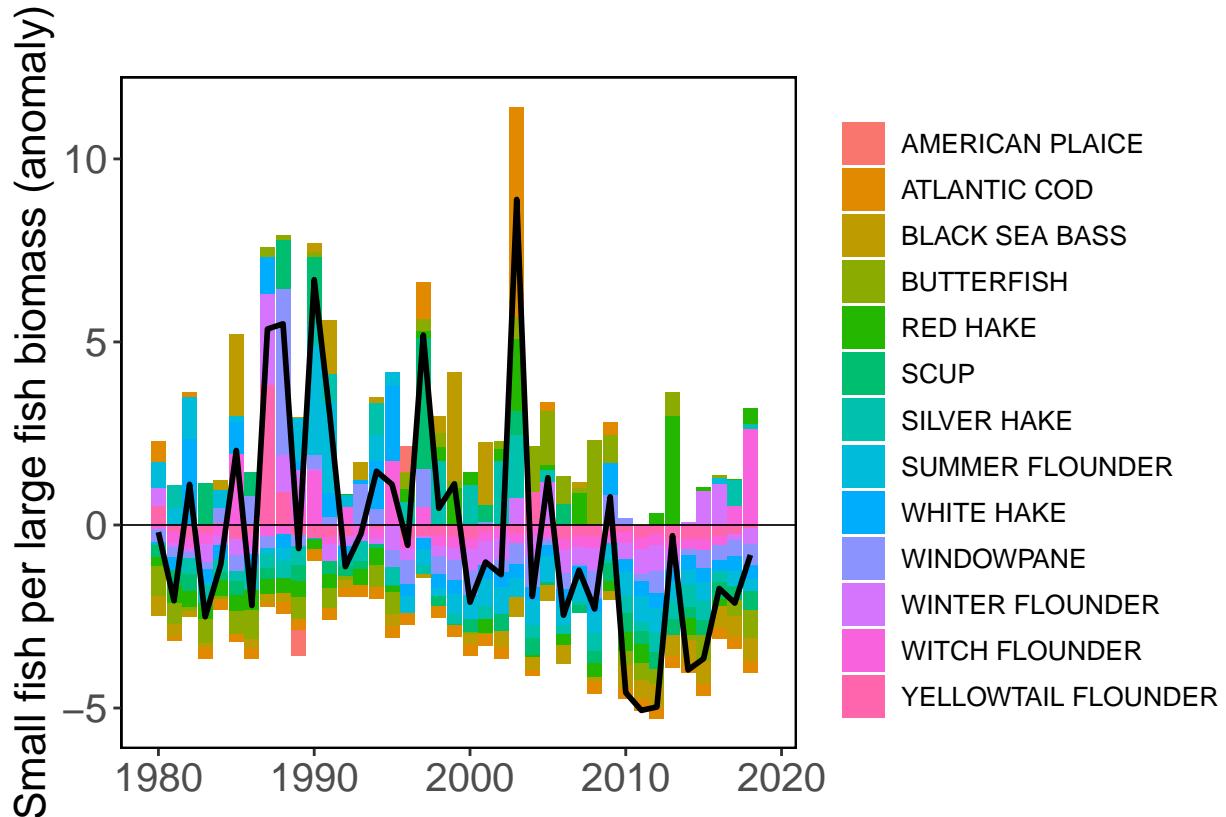


Figure 30.1: Groundfish productivity across all stocks in the Mid-Atlantic Bight.

Chapter 31

Recreational Fishing Indicators

Description: A variety of indicators derived from MRIP Recreational Fisheries Statistics, including total recreational catch, total angler trips by region, annual diversity of recreational fleet effort, and annual diversity of managed species.

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2017, 2018, 2019, 2020), State of the Ecosystem - Mid-Atlantic (2017, 2018, 2019, 2020)

Indicator category: Database pull with analysis

Contributor(s): Geret DePiper, Scott Steinbeck

Data steward: Geret DePiper, geret.depiper@noaa.gov

Point of contact: Geret DePiper, geret.depiper@noaa.gov

Public availability statement: Data sets are publicly available (see Data Sources below).

31.1 Methods

We used total recreational harvest as an indicator of seafood production and total recreational trips and total recreational anglers as proxies for recreational value generated from the Mid-Atlantic and New England regions respectively. We estimated both recreational catch diversity in species managed by the Fisheries Management Councils; Mid-Atlantic (MAFMC), New England (NEFMC) and Atlantic States (ASFMC) and fleet effort diversity using the effective Shannon index.

31.1.1 Data sources

All recreational fishing indicator data, including number of recreationally harvested fish, number of angler trips, and number of anglers, were downloaded from the Marine Recreational Information Program MRIP Recreational Fisheries Statistics Queries portal. Relevant metadata including information regarding data methodology updates are available at the query site. Note that 2017 data were considered preliminary at the time of the data pull.

Data sets were queried by region on the MRIP site, and for the purposes of the State of the Ecosystem reports, the “NORTH ATLANTIC” and “MID-ATLANTIC” regions were mapped to the New England and Mid-Atlantic report versions respectively. All query pages are accessible through the MRIP Recreational Fisheries Statistics site.

The number of recreationally harvested fish was found by selecting “TOTAL HARVEST (A + B1)” on the Catch Time Series Query page. Catch diversity estimates were also derived from the total catch time series (see below). Species included in the diversity of catch analysis included American eel *Anguilla rostrata*, Atlantic cod *Gadus morhua*, Atlantic mackerel *Scomber scombrus*, Atlantic sturgeon *Acipenser oxyrinchus*, black drum *Pogonias cromis*, black sea bass *Centropristes striata*, bluefish *Pomatomus saltatrix*, cobia *Rachycentron canadum*, haddock *Melanogrammus aeglefinus*, pollock *Pollachius virens*, red drum *Sciaenops ocellatus*, scup *Stenotomus chrysops*, Spanish mackerel *Scomberomorus maculatus*, spiny dogfish *Squalus acanthias*, spot *Leiostomus xanthurus*, spotted seatrout *Cynoscion nebulosus*, striped bass *Morone saxatilis*, summer flounder *Paralichthys dentatus*, tautog *Tautoga onitis*, tilefish *Lopholatilus chamaeleonticeps*, weakfish *Cynoscion regalis*, winter flounder *Pseudopleuronectes americanus*, and “All Other Species”.

Angler trips (listed as “TOTAL” trips) were pulled from the MRIP Effort Time Series Query page, and included data from 1981 - 2019. Time series of recreational fleet effort diversity were calculated from this data set (see below). The number of anglers was total number of anglers from the Marine Recreational Fishery Statistics Survey (MRFSS) Participation Time Series Query, and includes data from 1981 - 2016.

31.1.2 Data analysis

Recreational fleet effort diversity

Code used to for effort diversity data analysis can be found [here](#).

Recreational catch diversity

Code used to for catch diversity data analysis can be found [here](#).

31.1.3 Data processing

Recreational fishing indicators were formatted for inclusion in the `ecodata` R package using this code.

31.1.4 Plotting

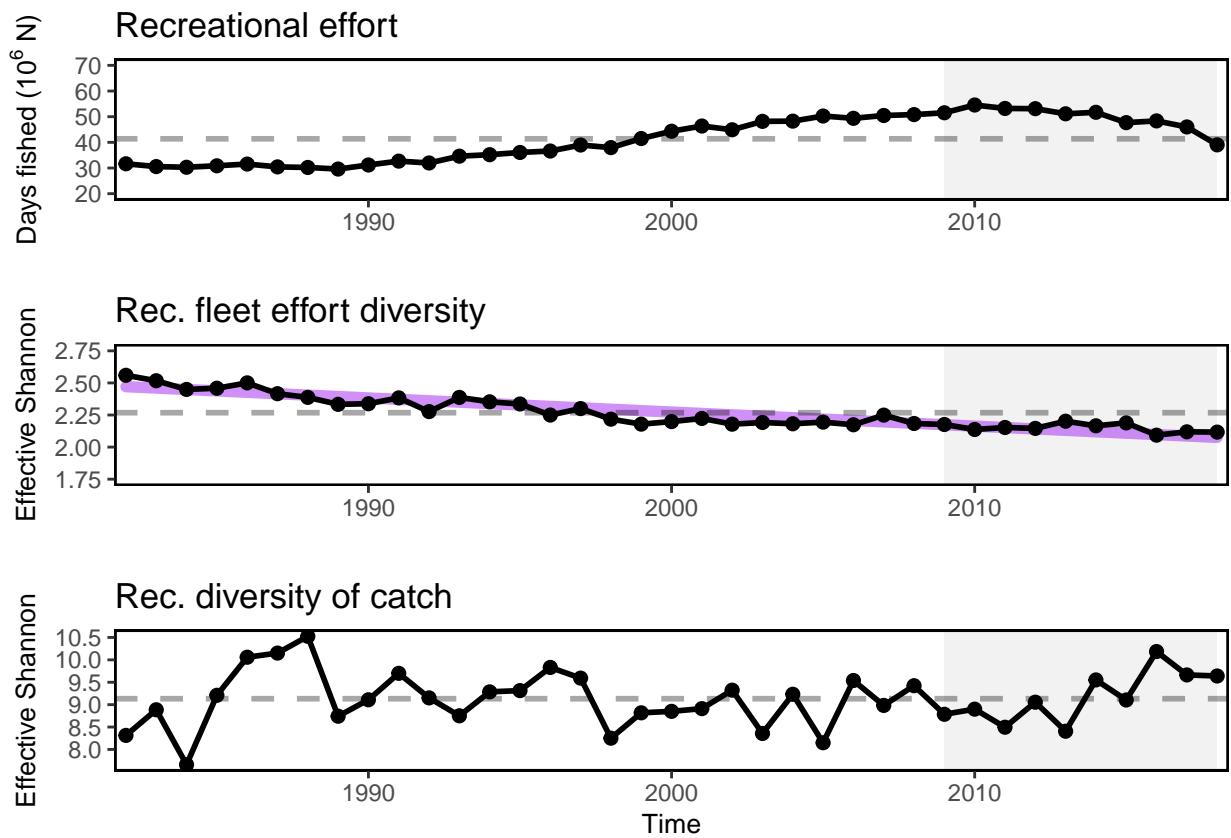


Figure 31.1: Recreational effort diversity and diversity of recreational catch in the Mid-Atlantic.

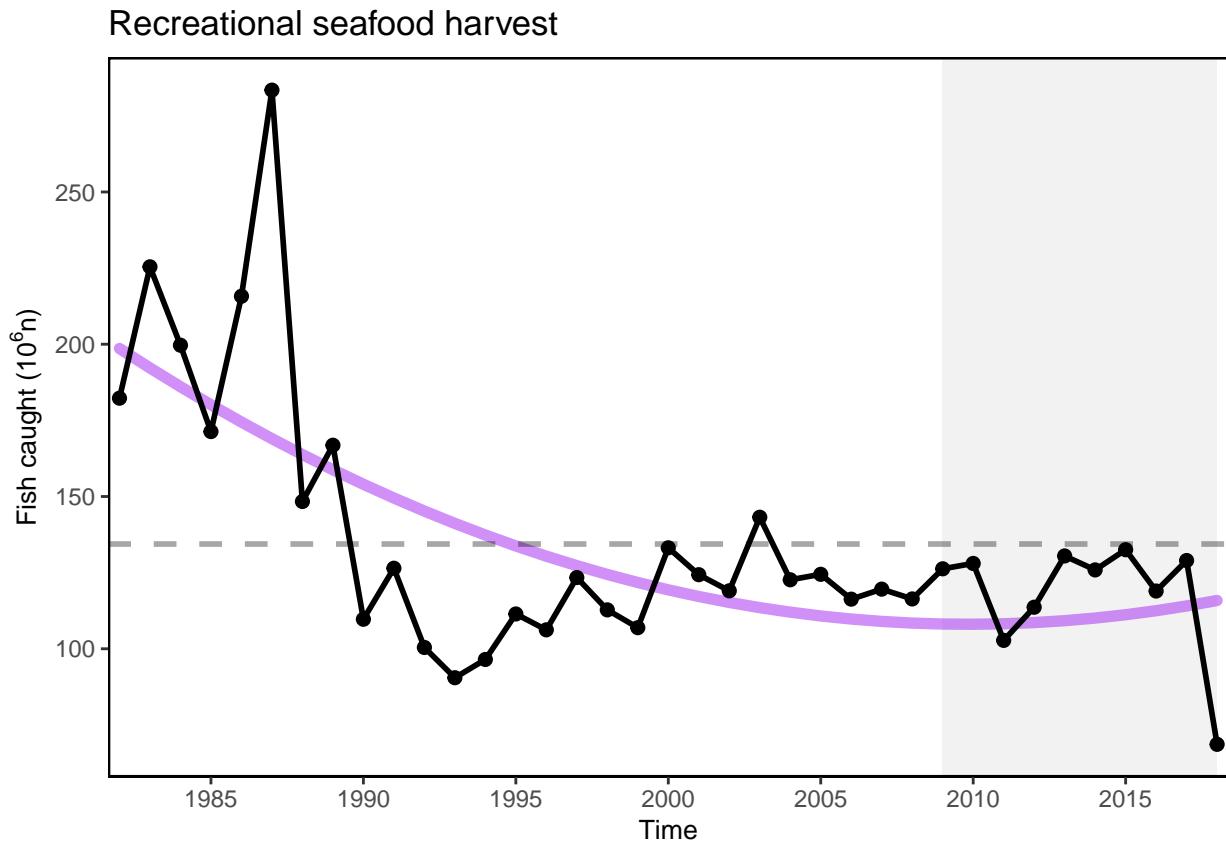


Figure 31.2: Total recreational seafood harvest in the Mid-Atlantic.

Chapter 32

Right Whale Abundance

Description: Right Whale

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2017, 2018, 2019, 2020), State of the Ecosystem - Mid-Atlantic (2017, 2018, 2019, 2020)

Indicator category: Synthesis of published information; Published methods

Contributor(s): Christopher D. Orphanides

Data steward: Chris Orphanides, chris.orphanides@noaa.gov

Point of contact: Richard Pace, richard.pace@noaa.gov

Public availability statement: Source data are available from the New England Aquarium upon request. Derived data are available here

32.1 Methods

32.1.1 Data sources

The North Atlantic right whale abundance estimates were taken from a published document (see Pace, Corkeron, and Kraus 2017), except for the most recent 2016 and 2017 estimates. Abundance estimates from 2016 and 2017 were taken from the 2016 National Oceanographic and Atmospheric Administration marine mammal stock assessment (Hayes et al. 2017) and an unpublished 2017 stock assessment.

Calves birth estimates are taken from a published report (Pettis, Pace, and Hamilton 2019) put out yearly by the North American Right Whale Consortium.

32.1.2 Data extraction

Data were collected from existing reports and validated by report authors.

32.1.3 Data analysis

Analysis for right whale abundance estimates is provided by Pace, Corkeron, and Kraus (2017), and code can be found in the supplemental materials.

32.1.4 Data processing

Time series of right whale and calf abundance estimates were formatted for inclusion in the `ecodata` R package using this R code.

32.1.5 Plotting

Code used to create the plots below can be found at these links, NARW population estimates and calf births.

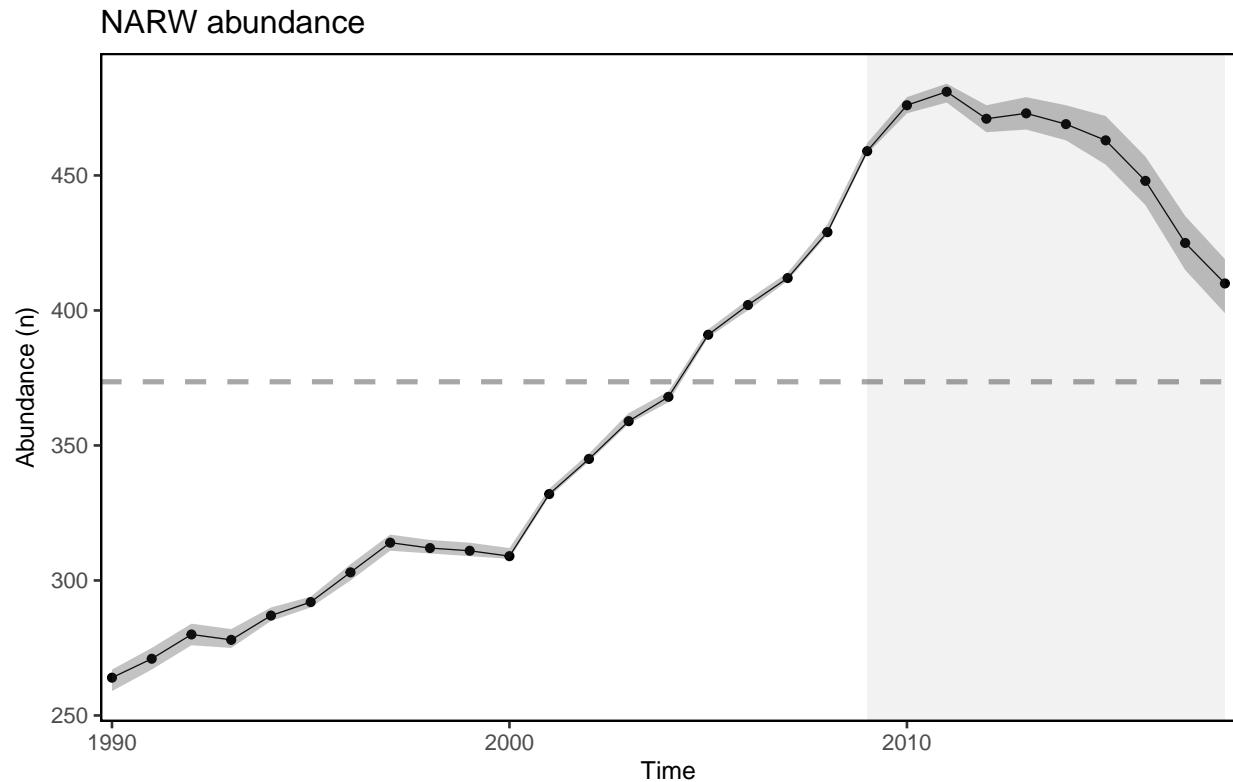


Figure 32.1: North Atlantic right whale population estimates shown with 95% credible intervals.

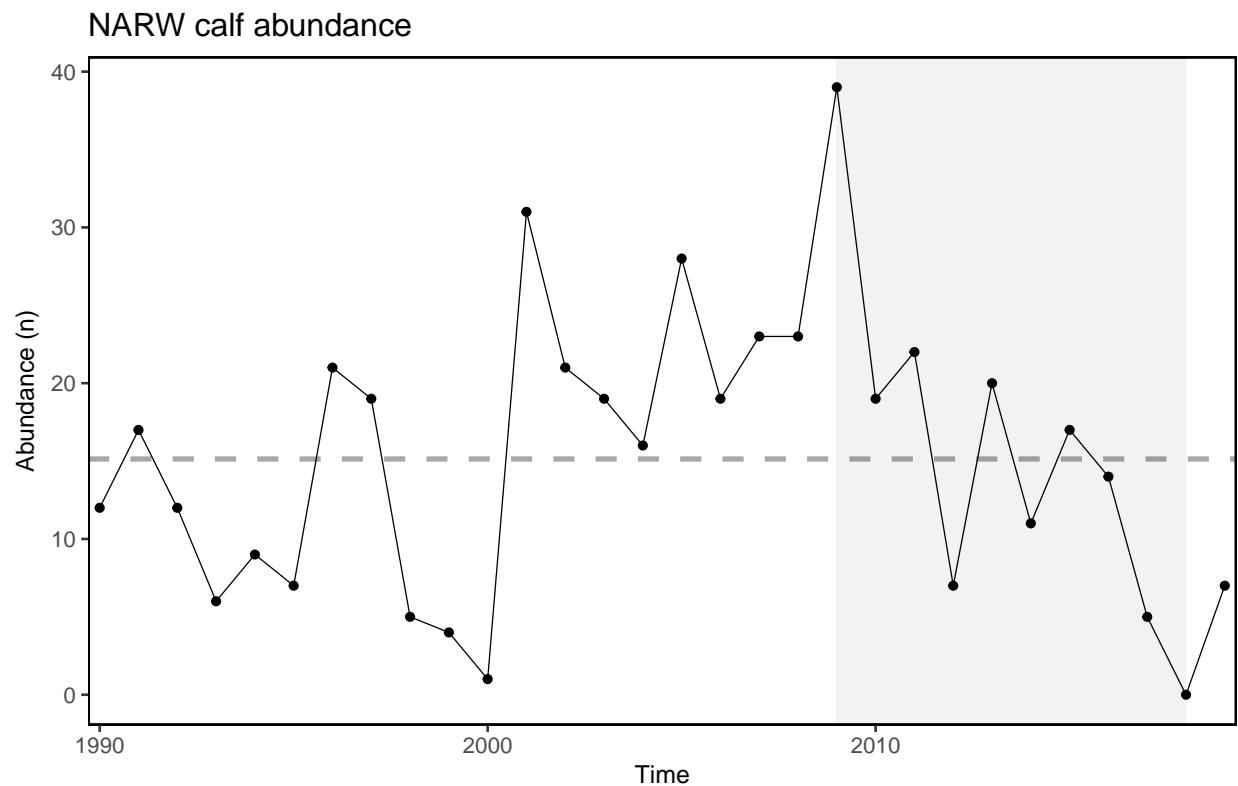


Figure 32.2: North Atlantic right whale calf births.

Chapter 33

SAFMC managed spp

Description: SAFMC Species on NES

Found in: State of the Ecosystem - Mid-Atlantic (2020)

Indicator category:

Contributor(s): Sean Lucey

Data steward: Kimberly Bastille kimberly.bastille@noaa.gov

Point of contact: Kimberly Bastille kimberly.bastille@noaa.gov

Public availability statement:

33.1 Methods

33.1.1 Data sources

33.1.2 Data extraction

33.1.3 Data analysis

33.1.4 Data processing

Blue runner (*Caranx cryos*) data were formatted for inclusion in the **ecodata** R package using this R code.

33.1.5 Plotting

The plot below was built using the code found [here](#).

Blue Runner Presence

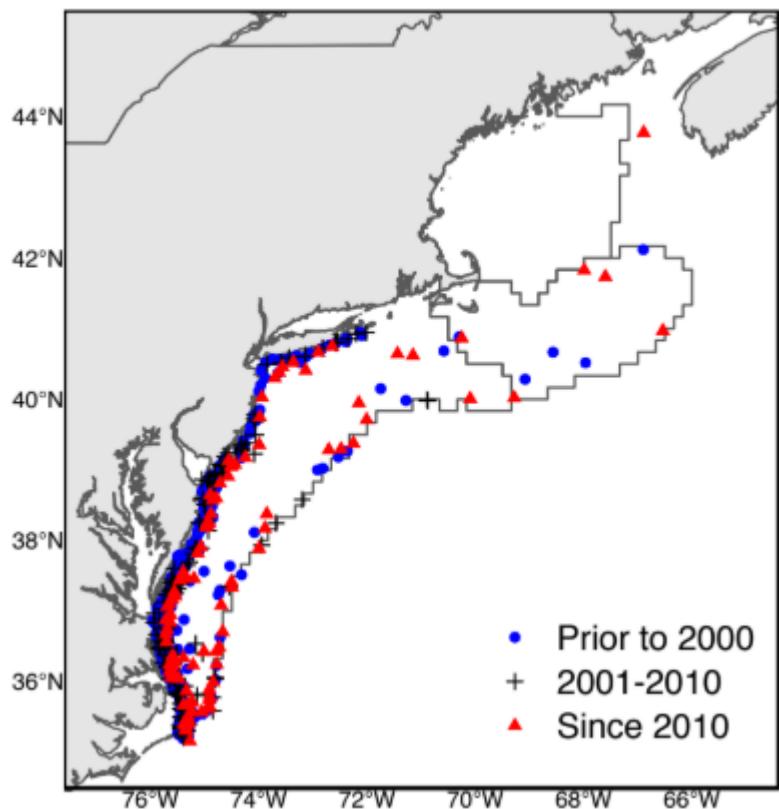


Figure 33.1: South Atlantic species Blue Runner Presence on the Northeast Shelf.

Chapter 34

NE Seabird diet and productivity

Description: Common tern annual diet and productivity at seven Gulf of Maine colonies managed by the National Audubon Society's Seabird Restoration Program

Indicator category: Published method

Found in: State of the Ecosystem - New England (2019, 2020)

Contributor(s): Don Lyons, Steve Kress, Paula Shannon, Sue Schubel

Data steward: Don Lyons, dlyons@audubon.org

Point of contact: Don Lyons, dlyons@audubon.org

Public availability statement: Please email dlyons@audubon.org for further information and queries on this indicator source data.

34.1 Methods

Chick diet

Common tern (*Sterna hirundo*) chick diet was quantified at each of the seven nesting sites (Fig. ??) by observing chick provisioning from portable observation blinds. The locations of observation blinds within each site were chosen to maximize the number of visible nests, and provisioning observations took place between mid-June and early August annually. Observations of chick diet were made during one or two, three to four hour periods throughout the day, but typically proceed according to nest activity levels (moreso in the morning hours). Observations began with chicks as soon as they hatched, and continue until the chicks fledged or died.

Most common tern prey species were identifiable to the species level due to distinct size, color and shape. However, when identification was not possible or was unclear, prey species were listed as “unknown” or “unknown fish”. More detailed methods can be found in Hall, Kress, and Griffin (2000).

Nest productivity

Common tern nest productivity, in terms of the number of fledged chicks per nest, was collected annually from fenced enclosures at island nesting sites (known as “productivity plots”). Newly hatched chicks within these enclosures were weighed, marked or banded, and observed until fledging, death, or until a 15 day period had passed when chicks were assumed to have fledged. Productivity was also quantified from observer blinds for nests outside of the productivity plots where chicks were marked for identification. More detailed methods for quantifying nest productivity can be found in Hall and Kress (2004)

34.1.1 Data sources

Common tern diet and nest productivity data were provided by the National Audubon Society's Seabird Restoration Program.

34.1.2 Data processing

Diet and productivity data were formatted for inclusion in the `ecodata` R package using this R code.

34.1.3 Data analysis

Raw diet data were used to create time series of mean shannon diversity through time and across study sites using the `vegan` R package (Oksanen et al. 2019). Code for this calculation can be found here. Diet diversity is presented along with nest productivity (+/- 1 SE).

Code used to create the figures below can be found at these links, diet diversity, prey frequencies and common tern productivity

34.1.4 Plotting

34.1.4.1 Diet diversity

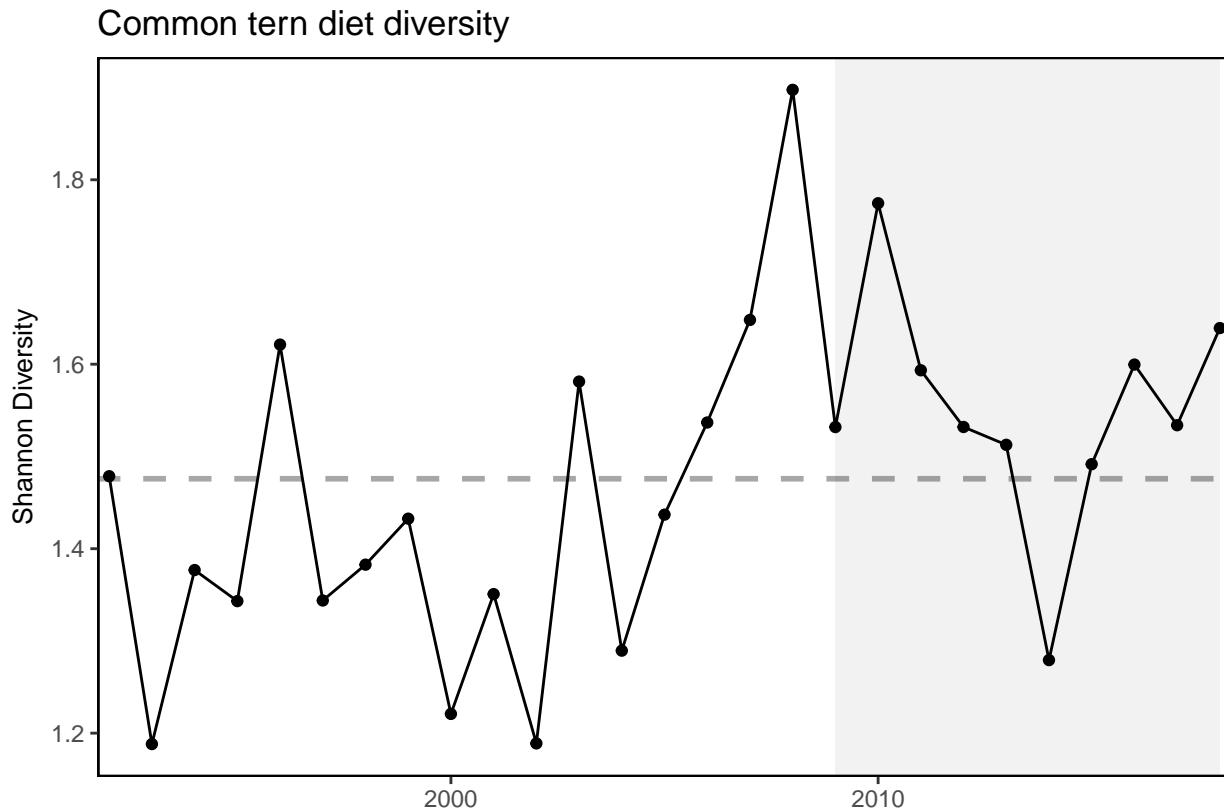


Figure 34.1: Shannon diversity of common tern diets observed at nesting sites in Gulf of Maine. Diversity of common tern diets has been predominantly above the long-term mean since 2006.

34.1.4.2 Prey frequencies

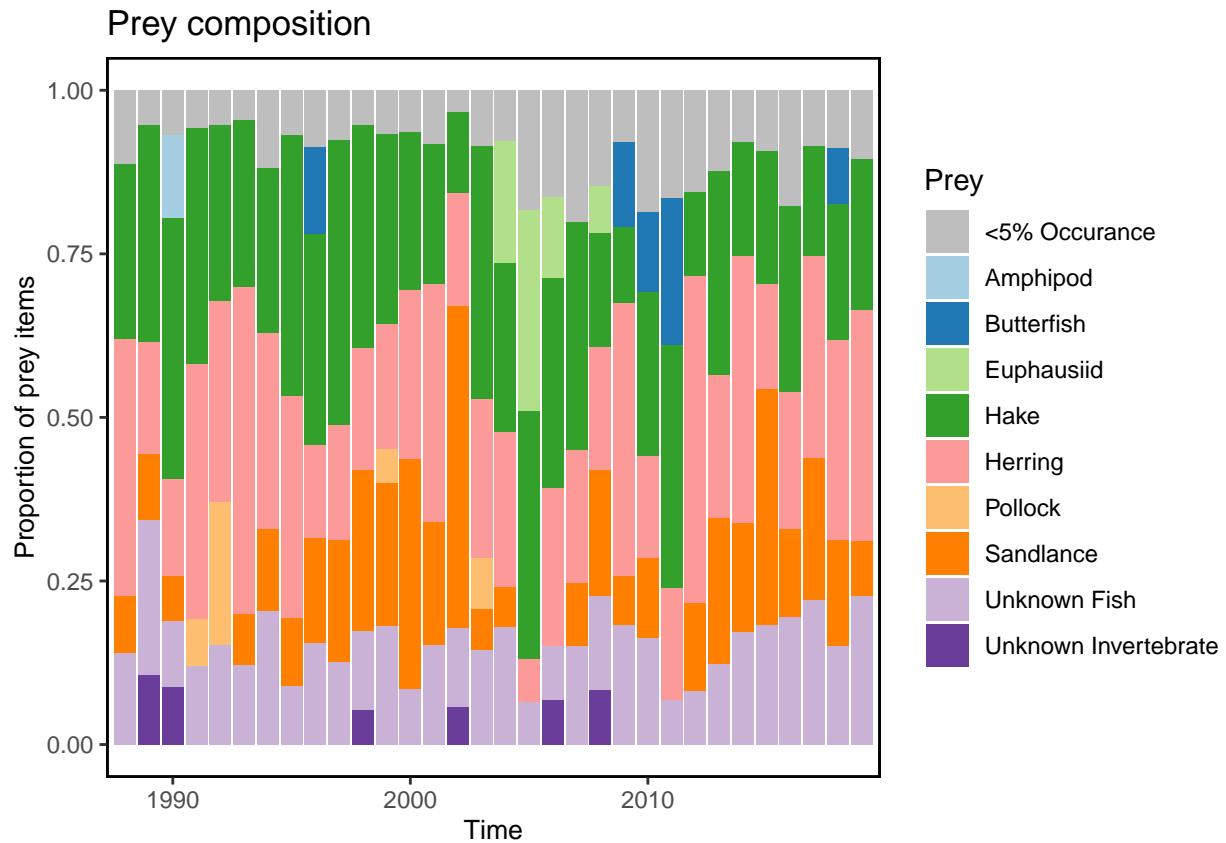


Figure 34.2: Prey frequencies in the diets of common tern observed across the seven colonies in the Gulf of Maine.

34.1.4.3 Common tern productivity

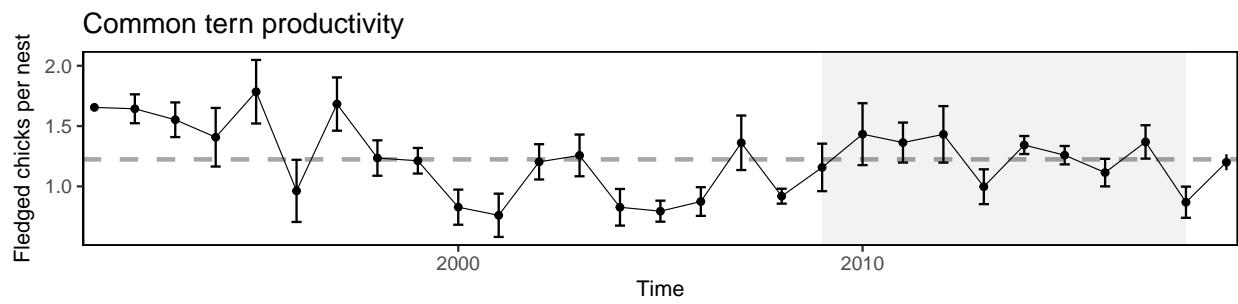


Figure 34.3: Common terns: Mean common tern productivity at nesting sites in Gulf of Maine. Error bars show ± 1 SE of the mean.

Chapter 35

MA waterbird productivity

Description: Virginia waterbird data

Indicator category: Published method

Found in: State of the Ecosystem - Mid-Atlantic (2020)

Contributor(s): Ruth Boettcher

Data steward: Kimberly Bastille kimberly.bastille@noaa.gov

Point of contact: Kimberly Bastille kimberly.bastille@noaa.gov

Public availability statement:

35.1 Methods

35.1.1 Data sources

Virginia colonial waterbird breeding pair population estimates derived from table 4 of “Status and distribution of colonial waterbirds in coastal Virginia: 2018 breeding season.” Center for Conservation Biology Technical Report Series, CCBTR-19-06. College of William and Mary & Virginia Commonwealth University, Williamsburg, VA. 28 pp. Available at: https://ccbbirds.org/wp-content/uploads/CCBTR-19-06_Colonial-waterbirds-in-coastal-Virginia-2018.pdf

35.1.2 Data processing

VA colonial waterbird data were formatted for inclusion in the `ecodata` R package using this R code.

35.1.3 Data analysis

NA

35.1.4 Plotting

Code used to create the figure below can be found here.

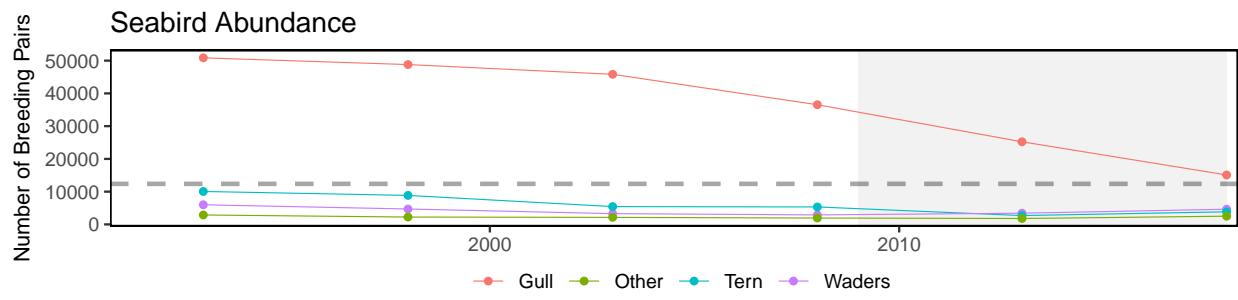


Figure 35.1: Functional group population estimated derived from Table 4 of Watts, B. D., B. J. Paxton, R. Boettcher, and A. L. Wilke. 2019.

Chapter 36

Seasonal SST Anomalies

Description: Seasonal SST Anomalies

Indicator category: Database pull with analysis

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018, 2019, 2020), State of the Ecosystem - Mid-Atlantic (2018, 2019, 2020)

Contributor(s): Sean Hardison, Vincent Saba

Data steward: Kimberly Bastille, kimberly.bastille@noaa.gov

Point of contact: Kimberly Bastille, kimberly.bastille@noaa.gov

Public availability statement: Source data are available here.

36.1 Methods

36.1.1 Data sources

Data for seasonal sea surface temperature anomalies (Fig. 36.1) were derived from the National Oceanographic and Atmospheric Administration optimum interpolation sea surface temperature high resolution data set (NOAA OISST V2) provided by NOAA Earth System Research Laboratory's Physical Science Division, Boulder, CO. The data extend from 1981 to present, and provide a $0.25^\circ \times 0.25^\circ$ global grid of SST measurements (Reynolds et al. 2007).

36.1.2 Data extraction

Individual files containing daily mean SST data for each year during the period of 1981-present were downloaded from the OI SST V5 site. Yearly data provided as layered rasters were masked according to the extent of Northeast US Continental Shelf. Data were split into three month seasons for (Winter = Jan, Feb, Mar; Spring = Apr, May, Jun; Summer = July, August, September; Fall = Oct, Nov, Dec).

36.1.3 Data analysis

We calculated the long-term mean (LTM) for each season-specific stack of rasters over the period of 1982-2010, and then subtracted the (LTM) from daily mean SST values to find the SST anomaly for a given year. The use of climatological reference periods is a standard procedure for the calculation of meteorological anomalies (WMO 2017). Prior to 2019 State of the Ecosystem reports, SST anomaly information made use

of a 1982-2012 reference period. A 1982-2010 reference period was adopted to facilitate calculating anomalies from a standard NOAA ESRL data set.

R code used in extraction and processing gridded and timeseries data can found in the `ecodata` package.

36.1.4 Plotting

Code used to build the figure below can be found [here](#).

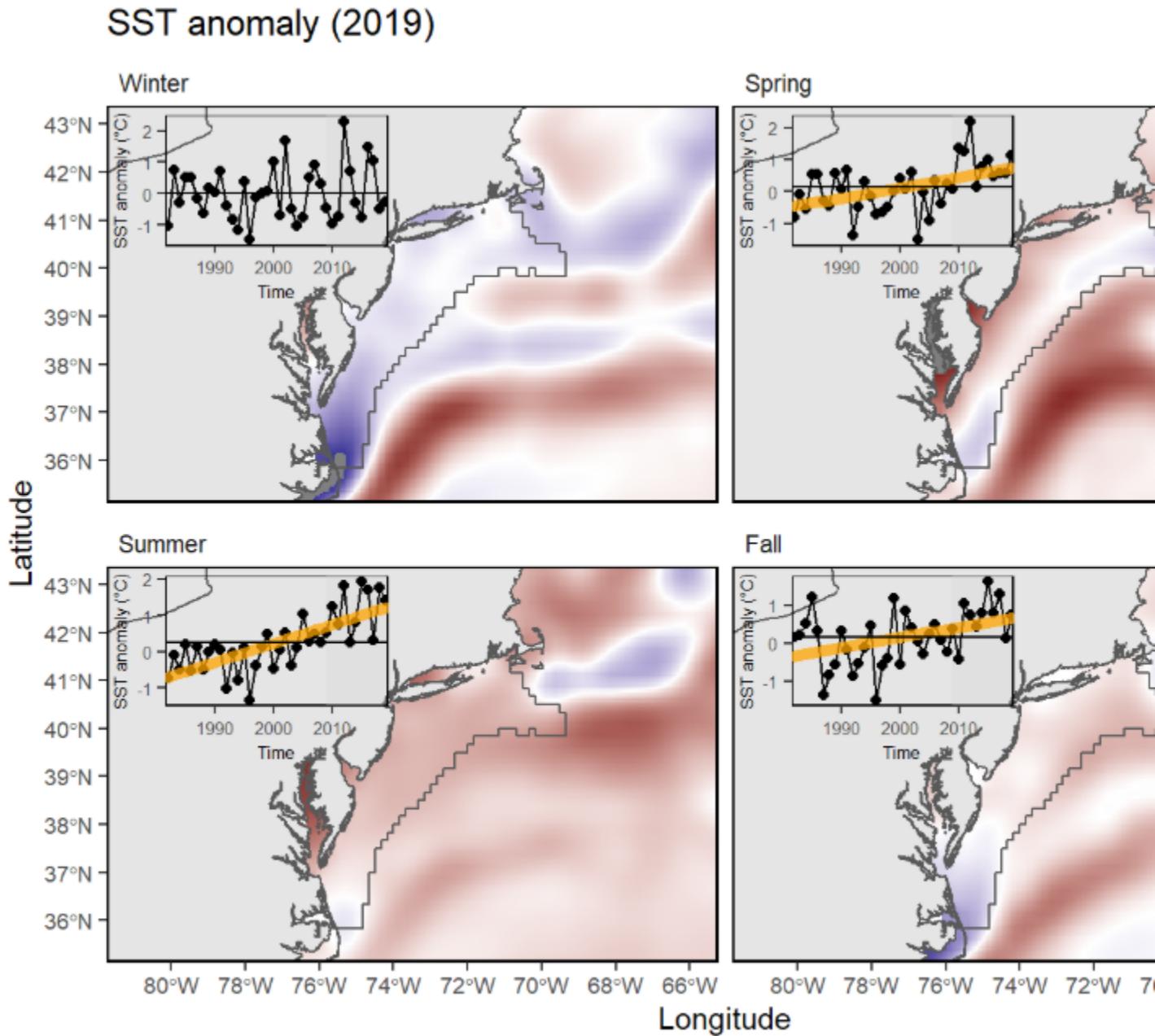


Figure 36.1: MAB seasonal sea surface temperature time series overlaid onto 2019 seasonal spatial anomalies.

Chapter 37

Single Species Status Indicator

Description: Summary of the most recent stock assessment results for each assessed species.

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2017, 2018, 2019, 2020), State of the Ecosystem - Mid-Atlantic (2017, 2018, 2019, 2020)

Indicator category: Synthesis of published information

Contributor(s): Sarah Gaichas, based on code and spreadsheets originally provided by Chris Legault

Data steward: Sarah Gaichas sarah.gaichas@noaa.gov

Point of contact: Sarah Gaichas sarah.gaichas@noaa.gov

Public availability statement: All stock assessment results are publicly available (see Data Sources). Summarized data are available here.

37.1 Methods

37.1.1 Data sources

“Data” used for this indicator are the outputs of stock assessment models and review processes, including reference points (proxies for fishing mortality limits and stock biomass targets and limits), and the current fishing mortality rate and biomass of each stock. The spreadsheet summarizes the most recent stock assessment updates for each species, which are available on the Northeast Fisheries Science Center (NEFSC) website at:
<https://www.nefsc.noaa.gov/saw/reports.html>
<https://www.nefsc.noaa.gov/publications/crd/crd1717/>

Additional assessments are reported directly to the New England Fishery Management Council (NEFMC):
<http://s3.amazonaws.com/nefmc.org/Document-2-SAFE-Report-for-Fishing-Year-2016.pdf>
http://s3.amazonaws.com/nefmc.org/4_NEFSC_SkateMemo_July_2017.pdf

37.1.2 Data extraction

Each assessment document was searched to find the following information (often but not always summarized under a term of reference to determine stock status in the executive summary):

- **B_{cur}:** current year biomass, (most often spawning stock biomass (SSB) or whatever units the reference points are in)
- **F_{cur}:** current year fishing mortality, F

- **Bref:** biomass reference point, a proxy of Bmsy (the target)
- **Fref:** fishing mortality reference point, a proxy of Fmsy

37.1.3 Data processing

R code used to process the stock status data set for inclusion in the `ecodata` R package can be found [here](#).

37.1.4 Data analysis

For each assessed species, Bcur is divided by Bref and Fcur is divided by Fref. They are then plotted for each species on an x-y plot, with Bcur/Bref on the x axis, and Fcur/Fref on the y axis.

37.1.5 Plotting

The script used to develop the figure in the State of the Ecosystem report can be found [here](#).

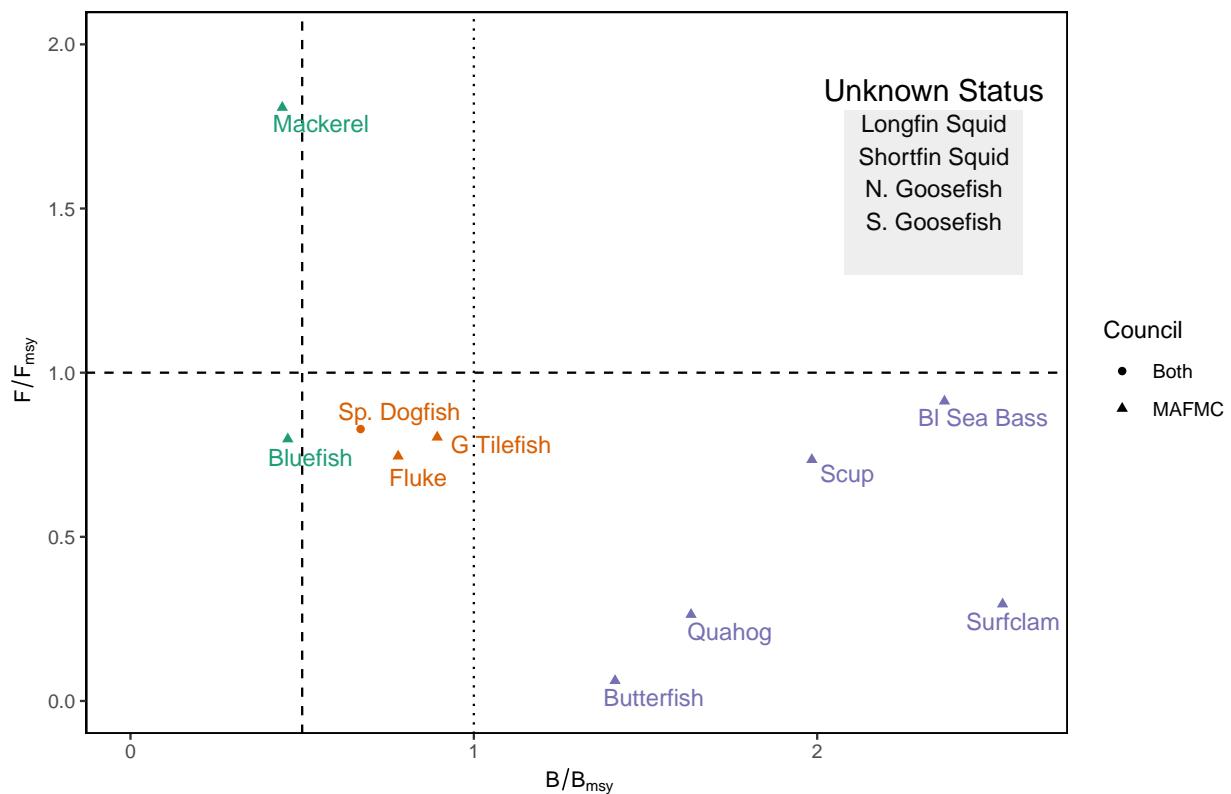


Figure 37.1: Summary of single species status for MAFMC and jointly managed stocks.

Chapter 38

Slopewater proportions

Description: Percent total of water type observed in the deep Northeast Channel (150-200 m water depth).

Indicator category: Published methods

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2019, 2020)

Contributors: Paula Fratantoni, paula.fratantoni@noaa.gov; David Mountain, NOAA Fisheries, retired.

Data steward: Kimberly Bastille, kimberly.bastille@noaa.gov

Point of contact: Paula Fratantoni, paula.fratantoni@noaa.gov

Public availability statement: Source data are publicly available at ftp://ftp.nefsc.noaa.gov/pub/hydro/matlab_files/yearly and in the World Ocean Database housed at <http://www.nodc.noaa.gov/OC5/SELECT/dbsearch/dbsearch.html> under institute code 258

38.1 Methods

38.1.1 Data sources

The slope water composition index incorporates temperature and salinity measurements collected on Northeast Fisheries Science Center surveys between 1977-present within the geographic confines of the Northeast Channel in the Gulf of Maine. Early measurements were made using water samples collected primarily with Niskin bottles at discreet depths, mechanical bathythermographs and expendable bathythermograph probes, but by 1991 the CTD – an acronym for conductivity temperature and depth – became standard equipment on all NEFSC surveys.

38.1.2 Data extraction

While all processed hydrographic data are archived in an Oracle database (OCDBS), we work from Matlab-formatted files stored locally.

38.1.3 Data analysis

Temperature and salinity measurements are examined to assess the composition of the waters entering the Gulf of Maine through the Northeast Channel. The analysis closely follows the methodology described by D. G. Mountain (2012). This method assumes that the waters flowing into the Northeast Channel between 150 and 200 meters depth are composed of slope waters, originating offshore of the continental shelf, and shelf waters, originating on the continental shelf south of Nova Scotia.

For each survey in the hydrographic archive, ocean temperature and salinity observations sampled in the area just inside the Northeast Channel (bounded by 42.2-42.6°latitude north and 66-66.8°longitude west) and between 150 - 200 meters depth are extracted and a volume-weighted average temperature and salinity is calculated. The volume weighting is accomplished by apportioning the area within the Northeast Channel polygon among the stations occupying the region, based on inverse distance squared weighting. The result of this calculation is a timeseries of volume-average temperature and salinity having a temporal resolution that matches the survey frequency in the database.

The average temperature and salinity observed at depth in the Northeast Channel is assumed to be the product of mixing between three distinct sources having the following temperature and salinity characteristics: (1) Warm Slope Water ($T=10\text{ }^{\circ}\text{C}$, $S=35$), (2) Labrador Slope Water ($T=6\text{ }^{\circ}\text{C}$, $S=34.7$) and (3) Scotian Shelf Water ($T=2\text{ }^{\circ}\text{C}$, $S=32$). As described by D. G. Mountain (2012), the relative proportion of each source is determined via a rudimentary 3-point mixing algorithm. On a temperature-salinity diagram, lines connecting the T-S coordinates for these three sources form a triangle, the sides of which represent mixing lines between the sources. A water sample that is a mixture of two sources will have a temperature and salinity that falls somewhere along the line connecting the two sources on the temperature-salinity diagram. Observations of temperature and salinity collected within the Northeast Channel would be expected to fall within the triangle if the water sampled is a mixture of the three sources. Simple geometry allows us to calculate the relative proportion of each source in a given measurement. As an example, a line drawn from the T-S point representing shelf water through an observed T-S in the center of the triangle will intersect the opposite side of the triangle (the mixing line connecting the coordinates of the two slope water sources). This intersecting T-S value may then be used to calculate the relative proportions (percentage) of the two slope water sources. Using this method, the percentage of Labrador slope water and Warm slope water are determined for the timeseries of volume-average temperature and salinity.

It should be noted that our method assumes that the temperature and salinity properties associated with the source watermasses are constant. In reality, these may vary from year to year, modified by atmospheric forcing, mixing and/or advective processes. Likewise, other sources are periodically introduced into the Northeast Channel, including intrusions of Gulf Stream water flowing into the Gulf of Maine and modified shelf water flowing out of the Gulf of Maine along the flank of Georges Bank. These sources are not explicitly considered in the 3-point mixing algorithm and may introduce errors in the proportional estimates. Code used to calculate slopewater proportions can be found [here](#).

38.1.4 Data processing

Source data were formatted for inclusion in the `ecodata` R package using the R code found [here](#).

38.1.5 Plotting

Code used to create the figure below can be found [here](#).

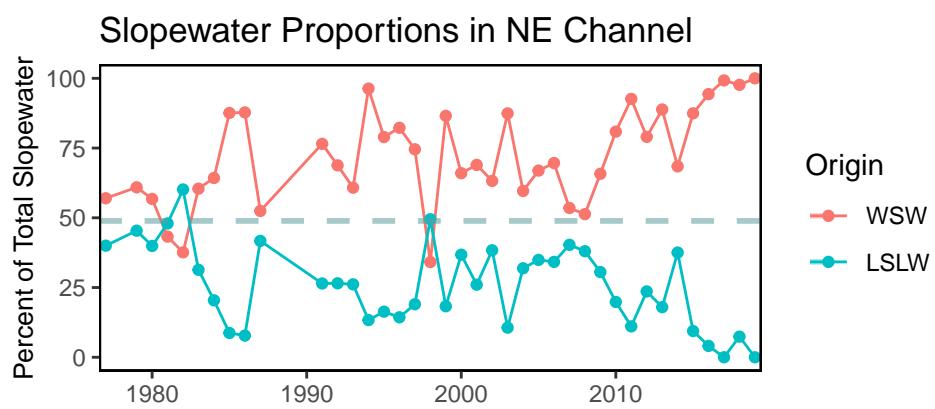


Figure 38.1: Proportion of warm slope water (WSW) and Labrador slope water (LSLW) entering the GOM through the Northeast Channel.

Chapter 39

Species Density Estimates

Description: Current and Historical Species Distributions

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2017, 2018), State of the Ecosystem - Mid-Atlantic (2017, 2018)

Indicator category: Database pull; Database pull with analysis

Contributor: Kevin Friedland

Data steward: Kevin Friedland

Point of contact: Kevin Friedland, kevin.friedland@noaa.gov

Public availability statement: Source data are publicly available.

39.1 Methods

We used kernel density plots to depict shifts in species' distributions over time. These figures characterize the probability of a species occurring in a given area based on Northeast Fisheries Science Center (NEFSC) Bottom Trawl Survey data. Kernel density estimates (KDEs) of distributions are shown for the period of 1970-1979 (shaded blue) and most recent three years of survey data (shaded red) (e.g. Figure 39.1). Results are typically visualized for spring and fall bottom trawl surveys separately.

Three probability levels (25%, 50%, 75%) are shown for each time period, where the 25% region depicts the core area of the distribution and the 75% region shows the area occupied more broadly by the species. A wide array of KDEs for many ecologically and economically important species on the Northeast US Continental Shelf are available [here](#).

39.1.1 Data sources

Current and historical species distributions are based on the NEFSC Bottom Trawl Survey data (aka "Survdat") and depth strata. Strata are available as shapefiles that can be downloaded [here](#) (listed as "strata.shp").

39.1.2 Data analysis

Code used for species density analysis can be found [here](#).

39.1.3 Plotting

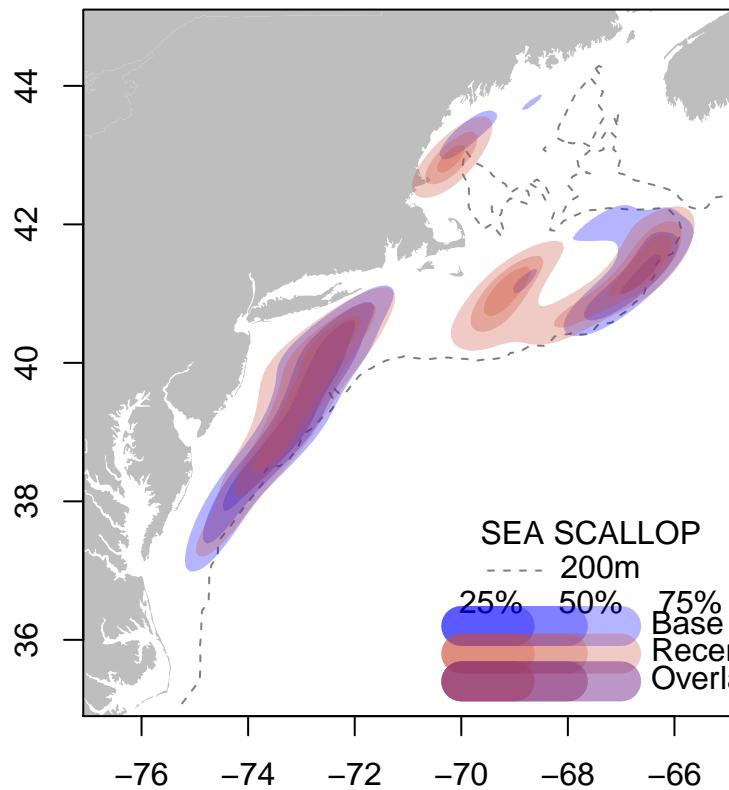


Figure 39.1: Current and historical sea scallop kernel density estimates derived from spring survey data. Current estimates derived from 2016-2018 data.

Chapter 40

Species Distribution Indicators

Description: Species mean depth, along-shelf distance, and distance to coastline

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2017, 2018, 2019, 2020), State of the Ecosystem - Mid-Atlantic (2017, 2018, 2019, 2020)

Indicator category: Extensive analysis; not yet published

Contributor(s): Kevin Friedland

Data steward: Kevin Friedland, kevin.friedland@noaa.gov

Point of contact: Kevin Friedland, kevin.friedland@noaa.gov

Public availability statement: Source data are available upon request ([read more here](#)). Derived data may be downloaded [here](#).

40.1 Methods

Three metrics quantifying spatial-temporal distribution shifts within fish populations were developed by Friedland et al. (2018), including mean depth, along-shelf distance, and distance to coastline. Along-shelf distance is a metric for quantifying the distribution of a species through time along the axis of the US Northeast Continental Shelf, which extends northeastward from the Outer Banks of North Carolina. Values in the derived time series correspond to mean distance in km from the southwest origin of the along-shelf axis at 0 km. The along-shelf axis begins at 76.53°W 34.60°N and terminates at 65.71°W 43.49°N.

Once mean distance is found, depth of occurrence and distance to coastline can be calculated for each species' positional center. Analyses present in the State of the Ecosystem (SOE) reports include mean depth and along-shelf distance for Atlantic cod, sea scallop, summer flounder, and black sea bass.

40.1.1 Data sources

Data for these indicators were derived from fishery-independent bottom trawl survey data collected by the Northeast Fisheries Science Center (NEFSC).

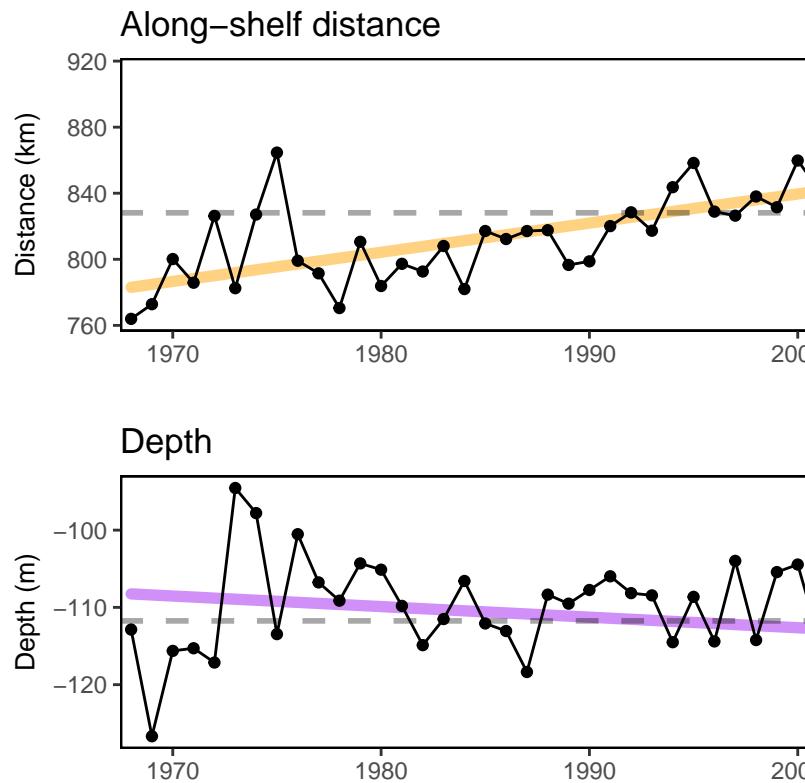
40.1.2 Data analysis

Species distribution indicators were derived using the R code found [here](#).

40.1.3 Data processing

Distribution indicators were further formatted for inclusion in the `ecodata` R package using the R code found here.

40.1.4 Plotting



Code used to create the figure below can be found [here](#).

Chapter 41

Stomach fullness

Description: Stomach Fullness

Found in: State of the Ecosystem - Mid-Atlantic (2020), State of the Ecosystem - New England (2020)

Indicator category:

Contributor(s): Laurel Smith

Data steward: Kimberly Bastille kimberly.bastille@noaa.gov

Point of contact: Kimberly Bastille kimberly.bastille@noaa.gov

Public availability statement:

41.1 Methods

41.1.1 Data sources

41.1.2 Data extraction

41.1.3 Data analysis

41.1.4 Data processing

41.1.5 Plotting

Fish stomach fullness index was formatted for inclusion in the `ecodata` R package using this R code.

41.1.6 Plotting

The plot below was built using the code found [here](#).

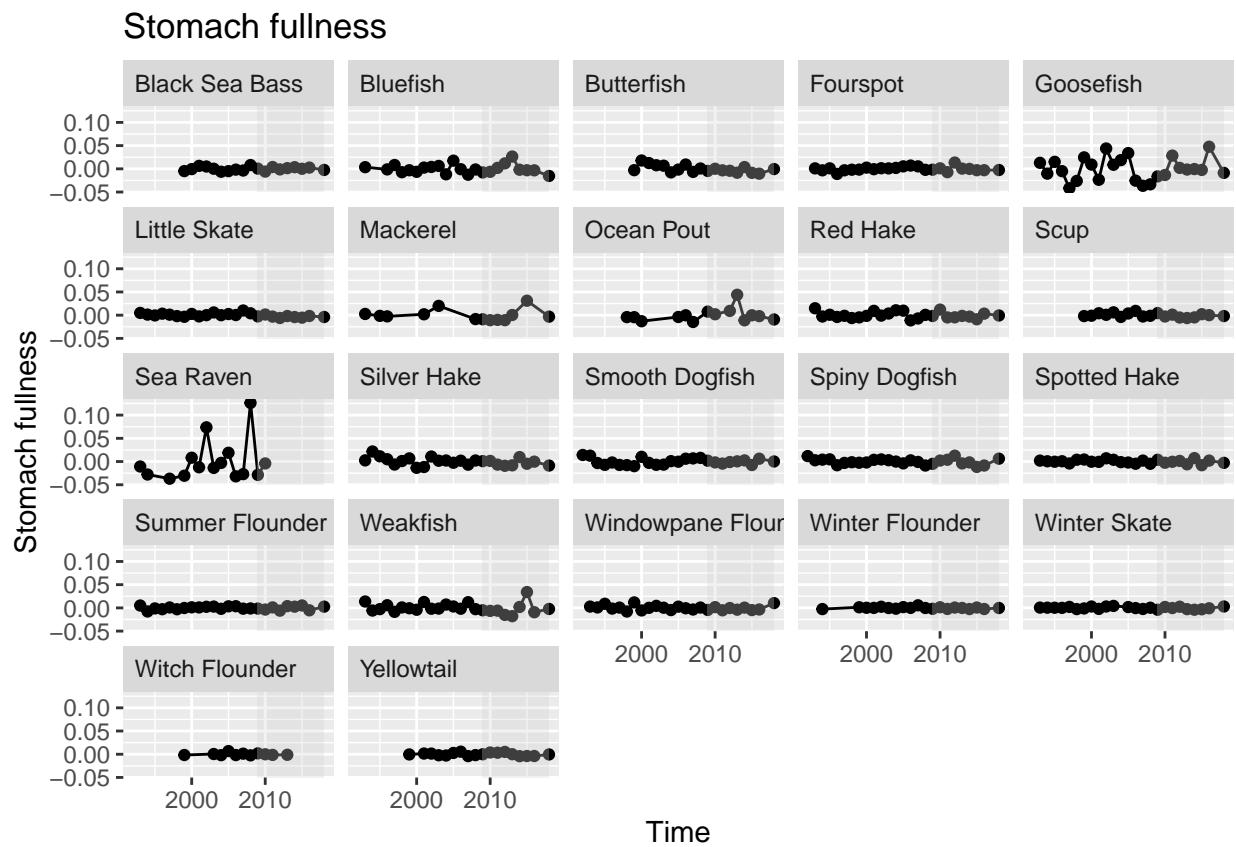


Figure 41.1: Stomach fullness anomaly.

Chapter 42

Survey Data

Description: Survdat (Survey database)

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2017, 2018, 2019, 2020), State of the Ecosystem - Mid-Atlantic (2017, 2018, 2019, 2020)

Indicator category: Database pull

Contributor(s): Sean Lucey

Data steward: Sean Lucey sean.lucey@noaa.gov

Point of contact: Sean Lucey sean.lucey@noaa.gov

Public availability statement: Source data are available to qualified researchers upon request (see “Access Information” here). Derived data used in SOE reports are available here.

42.1 Methods

The Northeast Fisheries Science Center (NEFSC) has been conducting standardized bottom trawl surveys in the fall since 1963 and spring since 1968. The surveys follow a stratified random design. Fish species and several invertebrate species are enumerated on a tow by tow basis (Azarovitz 1981).

The data are housed in the NEFSC’s survey database (SVDBS) maintained by the Ecosystem Survey Branch.

Direct pulls from the database are not advisable as there have been several gear modifications and vessel changes over the course of the time series (Miller et al. 2010). Survdat was developed as a database query that applies the appropriate calibration factors for a seamless time series since the 1960s. As such, it is the base for many of the other analyses conducted for the State of the Ecosystem report that involve fisheries independent data.

The Survdat script can be broken down into two sections. The first pulls the raw data from SVDBS. While the script is able to pull data from more than just the spring and fall bottom trawl surveys, for the purposes of the State of the Ecosystem reports only the spring and fall data are used. Survdat identifies those research cruises associated with the seasonal bottom trawl surveys and pulls the station and biological data. Station data includes tow identification (cruise, station, and stratum), tow location and date, as well as several environmental variables (depth, surface/bottom salinity, and surface/bottom temperature). Stations are filtered for representativeness using a station, haul, gear (SHG) code for tows prior to 2009 and a tow, operations, gear, and acquisition (TOGA) code from 2009 onward. The codes that correspond to a representative tow (SHG <= 136 or TOGA <= 1324) are the same used by assessment biologists at the

Table 42.1: Calibration factors for NEFSC trawl survey data

Name	Code	Applied
Door Conversion	DCF	<1985
Net Conversion	GCF	1973 - 1981 (Spring)
Vessel Conversion I	VCF	Delaware II records
Vessel Conversion II	BCF	Henry Bigelow records

NEFSC. Biological data includes the total biomass and abundance by species, as well as lengths and number at length.

The second section of the Survdat script applies the calibration factors. There are four calibrartion factors applied (Table 42.1). Calibration factors are pulled directly from SVDBS. Vessel conversions were made from either the NOAA Ship *Delaware II* or NOAA Ship *Henry Bigelow* to the NOAA Ship *Albatross IV* which was the primary vessel for most of the time series. The Albatross was decommissioned in 2009 and the Bigelow is now the primary vessel for the bottom trawl survey.

The output from Survdat is an RData file that contains all the station and biological data, corrected as noted above, from the NEFSC Spring Bottom Trawl Survey and NEFSC Fall Bottom Trawl Survey. The RData file is a data.table, a powerful wrapper for the base data.frame (<https://cran.r-project.org/web/packages/data.table/data.table.pdf>). There are also a series of tools that have been developed in order to utilize the Survdat data set (<https://github.com/sluey/RSurvey>).

42.1.1 Data sources

Survdat is a database query of the NEFSC survey database (SVDBS).These data are available to qualified researchers upon request. More information on the data request process is available under the “Access Information” field here.

42.1.2 Data extraction

Extraction methods are described above. The R code found here was used in the survey data extraction process.

42.1.3 Data analysis

The fisheries independent data contained within the Survdat is used in a variety of products; the more complicated analyses are detailed in their own sections. The most straightforward use of this data is for the resource species aggregate biomass indicators. For the purposes of the aggregate biomass indicators, fall and spring survey data are treated separately. Additionally, all length data is dropped and species seperated by sex at the catch level are merged back together.

For the aggregate biomass indicators, Survdat is first post stratified into Ecological Production Units. Stations are labeled by the EPU they fall within using the over function from the **rdga** R package (Bivand, Keitt, and Rowlingson 2018). Next, the total number of stations within each EPU per year is counted using unique station records. Biomass is summed by species per year per EPU. Those sums are divided by the appropriate station count to get the EPU mean. Finally, the mean biomasses are summed by aggregate groups. These steps are encompassed in the processing code, which also includes steps taken to format the data set for inclusion in the **ecodata** R package.

42.1.4 Plotting

Code used to create the figure below can be found [here](#)

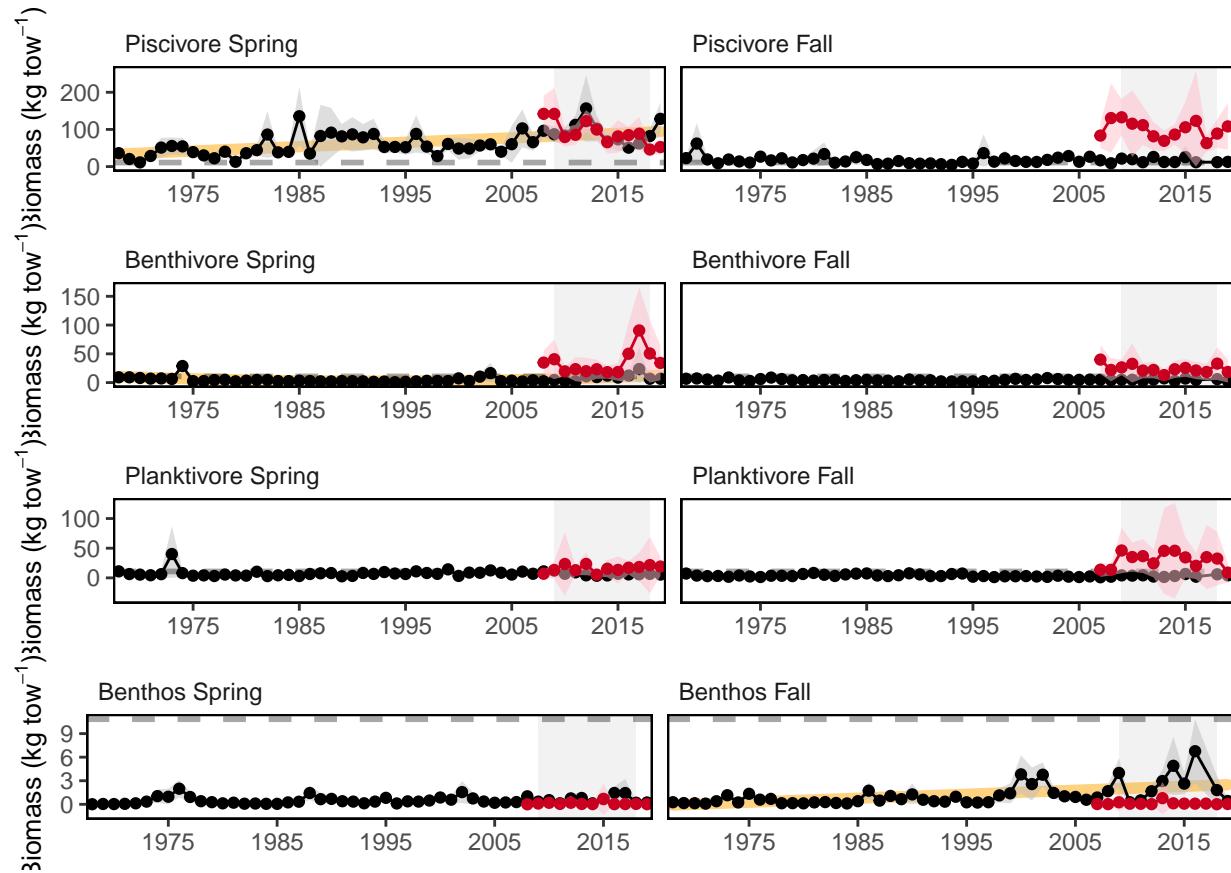


Figure 42.1: Spring (left) and fall (right) surveyed biomass in the Mid-Atlantic Bight. Data from the NEFSC Bottom Trawl Survey are shown in black, with NEAMAP shown in red.

Chapter 43

Thermal Habitat Projections

Description: Species Thermal Habitat Projections

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018), State of the Ecosystem - Mid-Atlantic (2018)

Indicator category: Published methods

Contributor(s): Vincent Saba

Data steward: Vincent Saba, vincent.saba@noaa.gov

Point of contact: Vincent Saba, vincent.saba@noaa.gov

Public availability statement: Source data are available to the public. Model outputs for thermal habitat projections are available here.

43.1 Methods

This indicator is based on work reported in Kleisner et al. (2017).

43.1.1 Data sources

43.1.1.1 Global Climate Model Projection

We used National Oceanographic and Atmospheric Administration's Geophysical Fluid Dynamics Laboratory (NOAA GFDL) CM2.6 simulation consisting of (1) a 1860 pre-industrial control, which brings the climate system into near-equilibrium with 1860 greenhouse gas concentrations, and (2) a transient climate response (2xCO₂) simulation where atmospheric CO₂ is increased by 1% per year, which results in a doubling of CO₂ after 70 years. The climate change response from CM2.6 was based on the difference between these two experimental runs. Refer to Saba et al. (2016) for further details.

43.1.1.2 Modeling Changes in Suitable Thermal Habitat

The NOAA Northeast Fisheries Science Center, U.S. Northeast Shelf (NES) bottom trawl survey, which has been conducted for almost 50-years in the spring and fall, provides a rich source of data on historical and current marine species distribution, abundance, and habitat, as well as oceanographic conditions (Azarovitz 1981). The survey was implemented to meet several objectives: (1) monitor trends in abundance, biomass, and recruitment, (2) monitor the geographic distribution of species, (3) monitor ecosystem changes, (4) monitor changes in life history traits (e.g., trends in growth, longevity, mortality, and maturation, and food

habits), and (5) collect baseline oceanographic and environmental data. These data can be leveraged for exploring future changes in the patterns of abundance and distribution of species in the region.

43.1.2 Data analysis

43.1.2.1 Global Climate Model Projection

The CM2.6 80-year projections can be roughly assigned to a time period by using the International Panel on Climate Change (IPCC) Representative Concentration Pathways (RCPs), which describe four different 21st century pathways of anthropogenic greenhouse gas emissions, air pollutant emissions, and land use (IPCC 2014). There are four RCPs, ranging from a stringent mitigation scenario (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0), and one scenario with very high greenhouse gas emissions (RCP8.5). For RCP8.5, the global average temperature at the surface warms by 2C by approximately 2060-2070 relative to the 1986-2005 climatology (see Figure SPM.7a in IPCC, 2013). For CM2.6, the global average temperature warms by 2C by approximately years 60-80 (see Fig. 1 in Winton et al. (2014)). Therefore, the last 20 years of the transient climate response simulation roughly corresponds to 2060-2080 of the RCP8.5 scenario.

Here, the monthly differences in surface and bottom temperatures ('deltas') for spring (February-April) and fall (September- November) are added to an average annual temperature climatology for spring and fall, respectively, derived from observed surface and bottom temperatures to produce an 80-year time series of future bottom and surface temperatures in both seasons. The observed temperatures come from the NEFSC spring and fall bottom trawl surveys conducted from 1968 to 2013 and represent approximately 30,000 observations over the time series.

43.1.2.2 Modeling Changes in Suitable Thermal Habitat

We modeled individual species thermal habitat across the whole U.S. NES and not by sub-region because we did not want to assume that species would necessarily maintain these assemblages in the future. Indeed, the goal here is to determine future patterns of thermal habitat availability for species on the U.S. NES in more broad terms. We fit one generalized additive model (GAM) based on both spring and fall data (i.e., an annual model as opposed to separate spring and fall models) and use it to project potential changes in distribution and magnitude of biomass separately for each season for each species. By creating a single annual model based on temperature data from both spring and fall, we ensure that the full thermal envelope of each species is represented. For example, if a species with a wide thermal tolerance has historically been found in cooler waters in the spring, and in warmer waters in the fall, an annual model will ensure that if there are warmer waters in the spring in the future, that species will have the potential to inhabit those areas. Additionally, because the trawl survey data are subject to many zero observations, we use delta-lognormal GAMs (Wood 2011), which model presence-absence separately from logged positive observations. The response variables in each of the GAMs are presence/absence and logged positive biomass of each assemblage or individual species, respectively. A binomial link function is used in the presence/absence models and a Gaussian link function is used in the models with logged positive biomass. The predictor variables are surface and bottom temperature and depth (all measured by the survey at each station), fit with penalized regression splines, and survey stratum, which accounts for differences in regional habitat quality across the survey region. Stratum may be considered to account for additional information not explicitly measured by the survey (e.g., bottom rugosity). Predictions of species abundance are calculated as the product of the predictions from the presence-absence model, the exponentiated predictions from the logged positive biomass model, and a correction factor to account for the retransformation bias associated with the log transformation (Duan 1983; and see Pinsky et al. 2013).

We calculated the suitable thermal habitat both in terms of changes in 'suitable thermal abundance', defined as the species density possible given appropriate temperature, depth and bathymetric conditions, and changes in 'suitable thermal area', defined as the size of the physical area potentially occupied by a species given appropriate temperature, depth and bathymetric conditions. Suitable thermal abundance is determined from the predictions from the GAMs (i.e., a prediction of biomass). However, this quantity should not be

interpreted directly as a change in future abundance or biomass, but instead as the potential abundance of a species in the future given changes in temperature and holding all else (e.g., fishing effort, species interactions, productivity, etc.) constant. Suitable thermal area is determined as a change in the suitable area that a species distribution occupies in the future and is derived from the area of the kernel density of the distribution. To ensure that the estimates are conservative, we select all points with values greater than one standard deviation above the mean. We then compute the area of these kernels using the `gArea` function from the `rgeos` package in R (Bivand et al. 2011).

43.1.3 Plotting

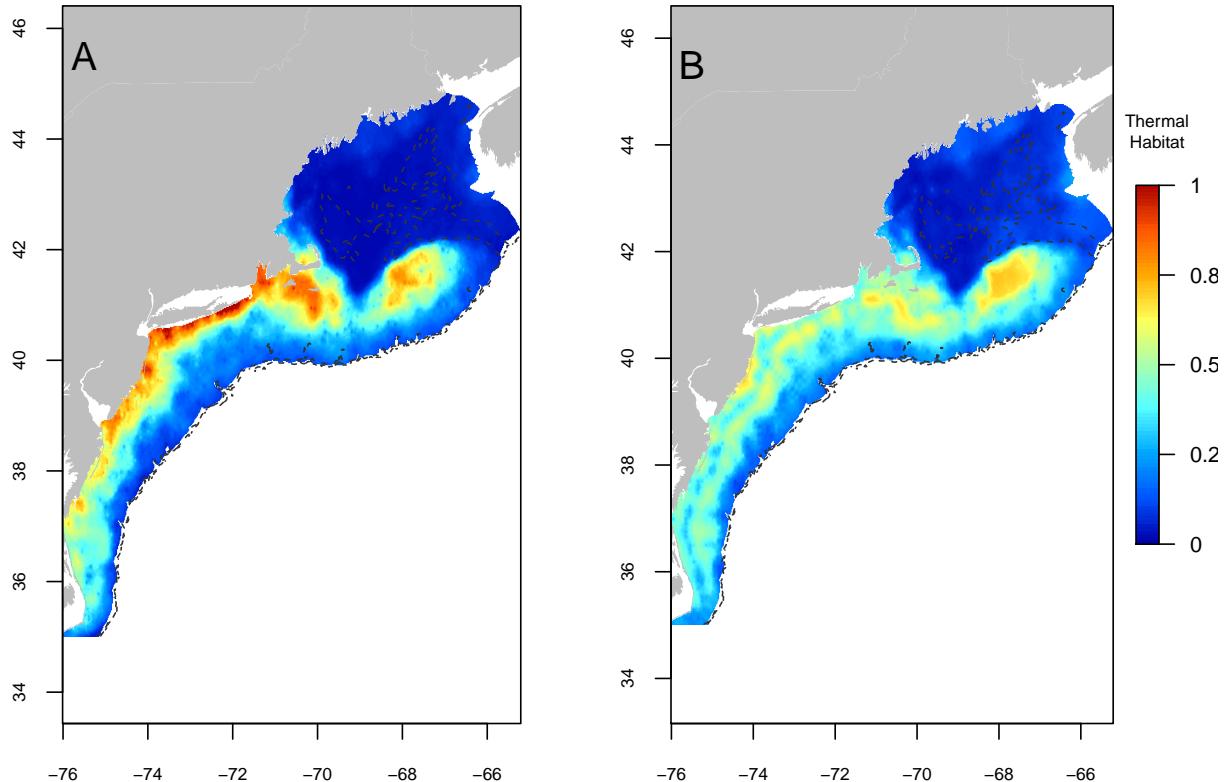


Figure 43.1: Current thermal habitat estimate (A), and 20-40 year thermal habitat projection (B) for summer flounder on the Northeast Continental Shelf.

Note: The thermal habitat model output for all species presented in State of the Ecosystem reports is accessible through the NEFSC ERDDAP server.

Chapter 44

Trend Analysis

Description: Time series trend analysis

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2018, 2019), State of the Ecosystem - Mid-Atlantic (2018, 2019)

Indicator category: Extensive analysis, not yet published

Contributor(s): Sean Hardison, Charles Perretti, Geret DePiper

Data steward: NA

Point of contact: Kimberly Bastille, kimberly.bastille@noaa.gov

Public availability statement: NA

44.1 Methods

Summarizing trends for ecosystem indicators is desirable, but the power of statistical tests to detect a trend is hampered by low sample size and autocorrelated observations (see Nicholson and Jennings 2004; Wagner et al. 2013; Storch 1999). Prior to 2018, time series indicators in State of the Ecosystem reports were presented with trend lines based on a Mann-Kendall test for monotonic trends to test significance ($p < 0.05$) of both long term (full time series) and recent (2007–2016) trends, although not all time series were considered for trend analysis due to limited series lengths. There was also concern that a Mann-Kendall test would not account for any autocorrelation present in State of the Ecosystem (SOE) indicators.

In a simulation study (Hardison et al. 2019), we explored the effect of time series length and autocorrelation strength on statistical power of three trend detection methods: a generalized least squares model selection approach, the Mann-Kendall test, and Mann-Kendall test with trend-free pre-whitening. Methods were applied to simulated time series of varying trend and autocorrelation strengths. Overall, when sample size was low ($N = 10$) there were high rates of false trend detection, and similarly, low rates of true trend detection. Both of these forms of error were further amplified by autocorrelation in the trend residuals. Based on these findings, we selected a minimum series length of $N = 30$ for indicator time series before assessing trend.

We also chose to use a GLS model selection (GLS-MS) approach to evaluate indicator trends in the 2018 (and future) State of the Ecosystem reports, as this approach performed best overall in the simulation study. GLS-MS also allowed for both linear and quadratic model fits and quantification of uncertainty in trend estimates. The model selection procedure for the GLS approach fits four models to each time series and selects the best fitting model using AICc. The models are, 1) linear trend with uncorrelated residuals, 2)

linear trend with correlated residuals, 3) quadratic trend with uncorrelated residuals, and 4) quadratic trend with correlated residuals. I.e., the models are of the form

$$Y_t = \alpha_0 + \alpha_1 X_t + \alpha_2 X_t^2 + \epsilon_t$$

$$\epsilon_t = \rho \epsilon_{t-1} + \omega_t$$

$$\omega_t \sim N(0, \sigma^2)$$

Where Y_t is the observation in time t , X_t is the time index, ϵ_t is the residual in time t , and ω_t is a normally distributed random variable. Setting $\alpha_2 = 0$ yields the linear trend model, and $\rho = 0$ yields the uncorrelated residuals model.

The best fit model was tested against the null hypothesis of no trend through a likelihood ratio test ($p < 0.05$). All models were fit using the R package `nlme` (Pinheiro et al. 2017) and AICc was calculated using the R package `AICcmodavg` (Mazerolle 2017). In SOE time series figures, significant positive trends were colored orange, and negative trends purple.

44.1.1 Data source(s)

NA

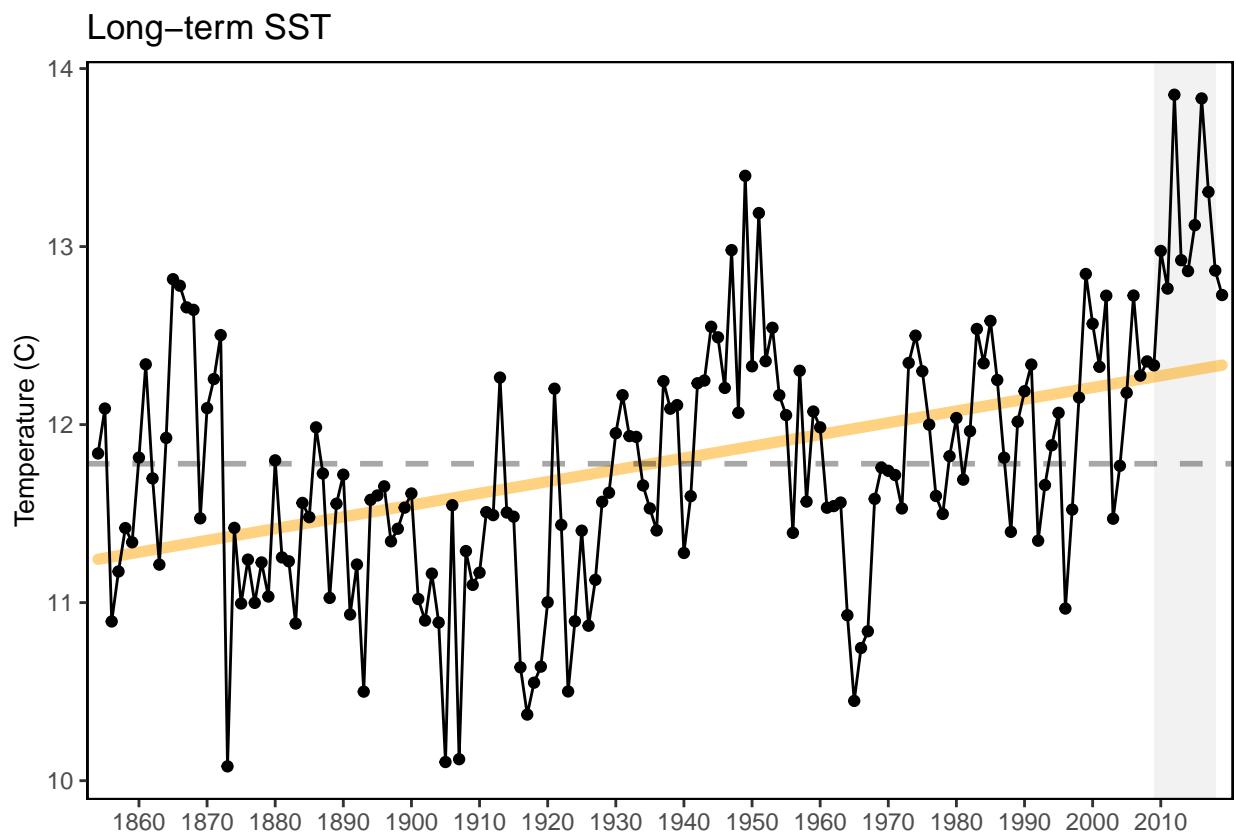
44.1.2 Data extraction

NA

44.1.3 Data analysis

Code used for trend analysis can be found [here](#).

Example plot



Chapter 45

Warm Core Rings

Description: Warm Core Rings

Found in: State of the Ecosystem - Mid-Atlantic (2020), State of the Ecosystem - New England (2020)

Indicator category:

Contributor(s): Kimberly Hyde

Data steward: Kimberly Bastille kimberly.bastille@noaa.gov

Point of contact: Kimberly Hyde kimberly.hyde@noaa.gov

Public availability statement:

45.1 Methods

45.1.1 Data sources

45.1.2 Data extraction

45.1.3 Data analysis

45.1.4 Data processing

Warm core ring data were formatted for inclusion in the `ecodata` R package using this R code.

45.1.5 Plotting

The plot below was built using the code found [here](#).

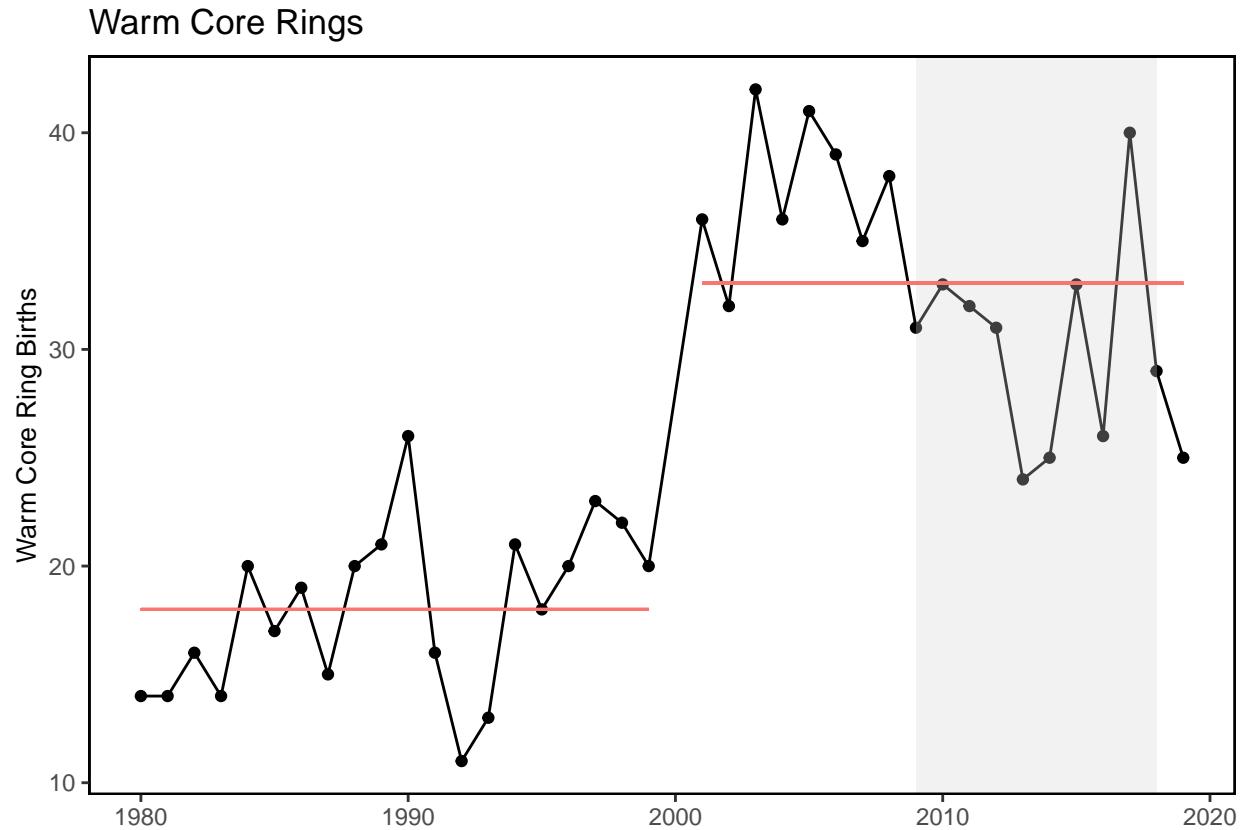


Figure 45.1: Interannual Variability of the WCR formation between 1980 and 2019. The regime shift (denoted by the split in the red solid line) is significant at the turn of the century. Figure reproduced with permission from Gangopadhyay, et al. (2019). 2018 and 2019 data points based on personal communication with A. Gangopadhyay (2020).

Chapter 46

Wind lease areas and habitat occupancy overlap

Description: Wind lease areas and habitat occupancy

Found in: State of the Ecosystem - Mid-Atlantic (2020)

Indicator category: Database pull with analysis; Extensive analysis; not yet published; Published methods

Contributor(s): Kevin Friedland

Data steward: Kimberly Bastille kimberly.bastille@noaa.gov

Point of contact: Kimberly Bastille kimberly.bastille@noaa.gov

Public availability statement: Source data are publicly available.

46.1 Methods

Habitat area with a probability of occupancy greater than 0.5 was modeled for many species throughout the Northeast Large Marine Ecosystem (NE-LME) (Friedland et al. 2020). Methodology for habitat occupancy models have been discussed in a separate chapter.

Bureau of Ocean Energy Management (BOEM) is the department responsible for the development of offshore wind energy. Existing and proposed lease areas were overlayed with habitat occupancy models to determine the species most likely to be found in the wind lease areas (Table 46.1).

46.1.1 Data extraction

BOEM existing and proposed lease areas (as of Feb 2019) shape files were taken from the BOEM website (Figure 46.1).

46.1.2 Data analysis

For the purposes of this indicator, the Northeast Shelf was broken into three general areas (North, Mid and South) (Figure 46.1). The species shown in the table below (Table 46.1) are those that have the highest average probability of occupancy in the lease areas.

46.1.3 Data processing

Code used to format wind lease area and habitat occupancy overlap for inclusion in the `ecodata` package can be found [here](#).

46.1.4 Plotting

Code used to build the table and figure below.

Table 46.1: Species with highest probability of occupancy species each season and area, with observed trends

Season	Existing - North		Proposed - North		Existing - Mid		Proposed - Mid		Existing - South	
	Species	Trend	Species	Trend	Species	Trend	Species	Trend	Species	Trend
Spring	Little Skate	↗	Atlantic Herring		Little Skate	↗	Spiny Dogfish	↗	Spiny Dogfish	↗
Spring	Atlantic Herring	↘	Little Skate	↗	Atlantic Herring	↘	Atlantic Herring	↘	Longfin Squid	↗
Spring	Windowpane	↗	Longhorn Sculpin	↗	Spiny Dogfish	↗	Little Skate	↗	Summer Flounder	↗
Spring	Winter Skate	↗	Windowpane	↗	Windowpane	↗	Alewife	↘	Clearnose Skate	↗
Spring	Longhorn Sculpin	↗	Alewife	↘	Winter Skate	↗	Silver Hake	↗	Spotted Hake	↗
Fall	Butterfish	↗	Butterfish	↗	Summer Flounder	↗	Longhorn Sculpin	↗	Longfin Squid	↘
Fall	Longfin Squid	↗	Fourspot Flounder		Longfin Squid	↗	Little Skate	↗	Northern Searobin	↗
Fall	Summer Flounder	↗	Longhorn Sculpin	↘	Butterfish	↗	Butterfish	↗	Clearnose Skate	↗
Fall	Winter Flounder	↘	Summer Flounder	↗	Smooth Dogfish	↗	Sea Scallop	↗	Butterfish	↗
Fall	Spiny Dogfish	↘	Spiny Dogfish	↘	Windowpane	↗	Fourspot Flounder	↗	Spiny Dogfish/Spotted Hake	↗

BOEM lease areas

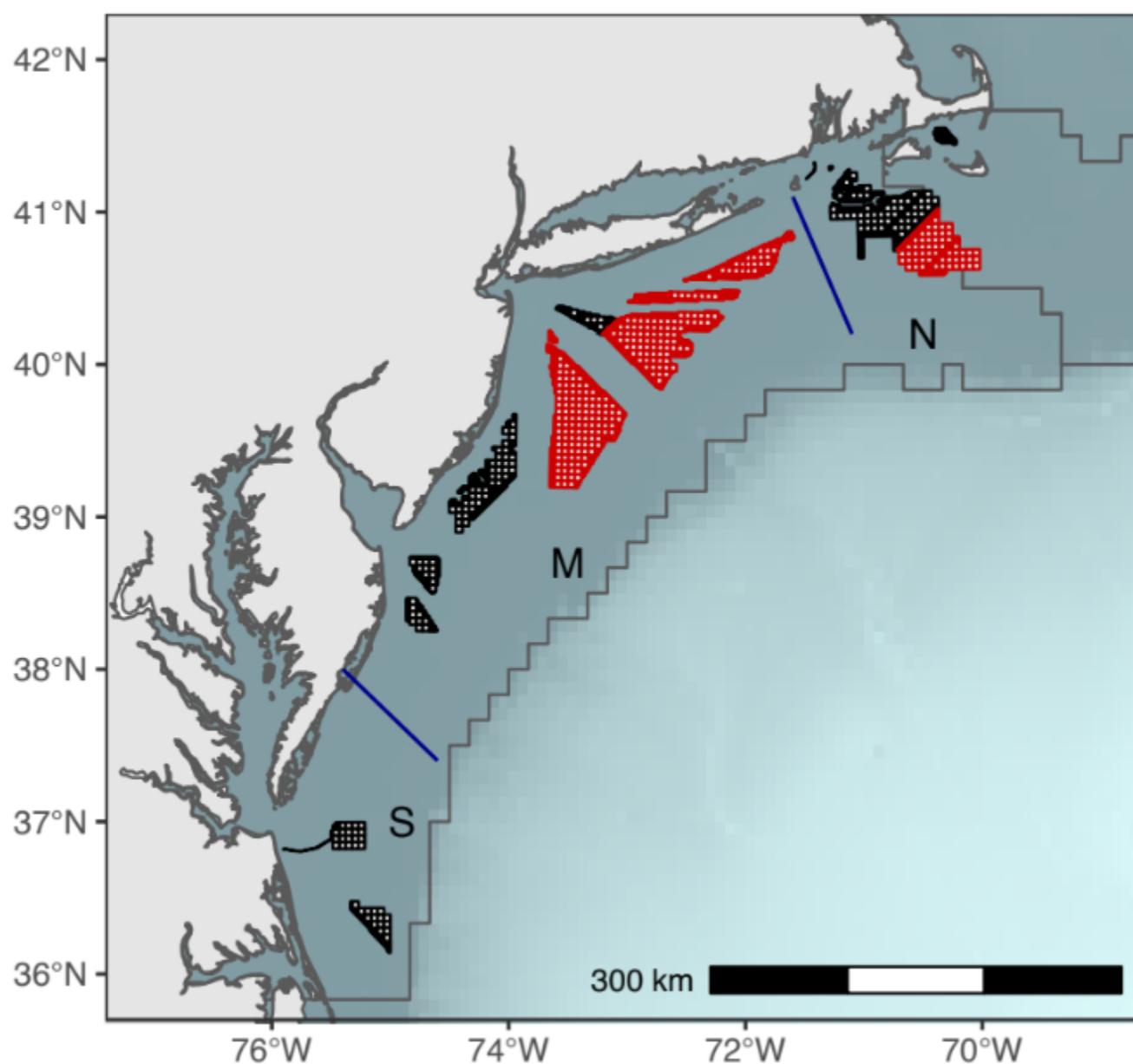


Figure 46.1: Map of BOEM existing (black) and proposed (red) lease areas as of February 2019.

Chapter 47

Zooplankton

Description: Annual time series of zooplankton abundance

Found in: State of the Ecosystem - Gulf of Maine & Georges Bank (2017, 2018, 2019, 2020), State of the Ecosystem - Mid-Atlantic (2017, 2018, 2019, 2020)

Indicator category: Database pull with analysis; Synthesis of published information; Extensive analysis, not yet published; Published methods

Contributor(s): Ryan Morse, Kevin Friedland

Data steward: Harvey Walsh, harvey.walsh@noaa.gov; Mike Jones, michael.jones@noaa.gov

Point of contact: Ryan Morse, ryan.morse@noaa.gov; Harvey Walsh, harvey.walsh@noaa.gov; Kevin Friedland, kevin.friedland@noaa.gov

Public availability statement: Source data are publicly available here. Derived data can be found here.

47.1 Methods

47.1.1 Data sources

Zooplankton data are from the National Oceanographic and Atmospheric Administration Marine Resources Monitoring, Assessment and Prediction (MARMAP) program and Ecosystem Monitoring (EcoMon) cruises detailed extensively in Kane (2007), Kane (2011), and Morse et al. (2017).

47.1.2 Data extraction

Data are from the publicly available zooplankton dataset on the NOAA File Transfer Protocol (FTP) server. The excel file has a list of excluded samples and cruises based on Kane (2007) and Kane (2011).

R code used in extraction process.

```
# load data
URL = "ftp://ftp.nefsc.noaa.gov/pub/hydro/zooplankton_data/EcoMon_Plankton_Data_v3_0.xlsx"
ZPD = openxlsx::read.xlsx(URL, sheet = "Data")
```

47.1.3 Data analysis

Annual abundance anomalies

Data are processed similarly to Kane (2007) and Perretti et al. (2017b), where a mean annual abundance by date is computed by area for each species meeting inclusion metrics set in Morse et al. (2017). This is accomplished by binning all samples for a given species to bi-monthly collection dates based on median cruise date and taking the mean, then fitting a spline interpolation between mean bi-monthly abundance to give expected abundance on any given day of the year.

Code used for zooplankton data analysis can be found [here](#).

Copepod

Abundance anomalies (Figure 47.1) are computed from the expected abundance on the day of sample collection. Abundance anomaly time series are constructed for *Centropages typicus*, *Pseudocalanus* spp., *Calanus finmarchicus*, and total zooplankton biovolume. The small-large copepod size index is computed by averaging the individual abundance anomalies of *Pseudocalanus* spp., *Centropages hamatus*, *Centropages typicus*, and *Temora longicornis*, and subtracting the abundance anomaly of *Calanus finmarchicus*. This index tracks the overall dominance of the small bodied copepods relative to the largest copepod in the Northeast U.S. region, *Calanus finmarchicus*.

Euphausiids and Cnidarians

Stratified abundance of euphausiids and cnidarians were included in the 2020 State of the Ecosystem reports (Figure 47.2). These were calculated as the log of estimated absolute number of individuals.

Seasonal abundance

Time series of zooplankton abundance in the spring and fall months have been presented in the 2019 Mid-Atlantic State of the Ecosystem report. Raw abundance data were sourced from the EcoMon cruises referenced above, and ordinary kriging was used to estimate seasonal abundance over the Northeast Shelf. These data were then aggregated further into time series of mean abundance by Ecological Production Unit.

Zooplankton Diversity

Time series of zooplankton diversity (effective shannon) (Figure 47.3) was calculated using 42 zooplankton classifications collected from the EcoMon cruises, referenced above.

47.1.4 Data processing

Zooplankton abundance indicators were formatted for inclusion in the `ecodata` R package using the code at these links, abundance anomaly and seasonal abundance

47.1.5 Plotting

Code used to create the figures below can be found [linked here](#), copepod abundance (47.1), Euphausiid and Cnidarian abundance (47.2) and zooplankton diversity (47.3).

Abundance anomaly

Zooplankton Diversity

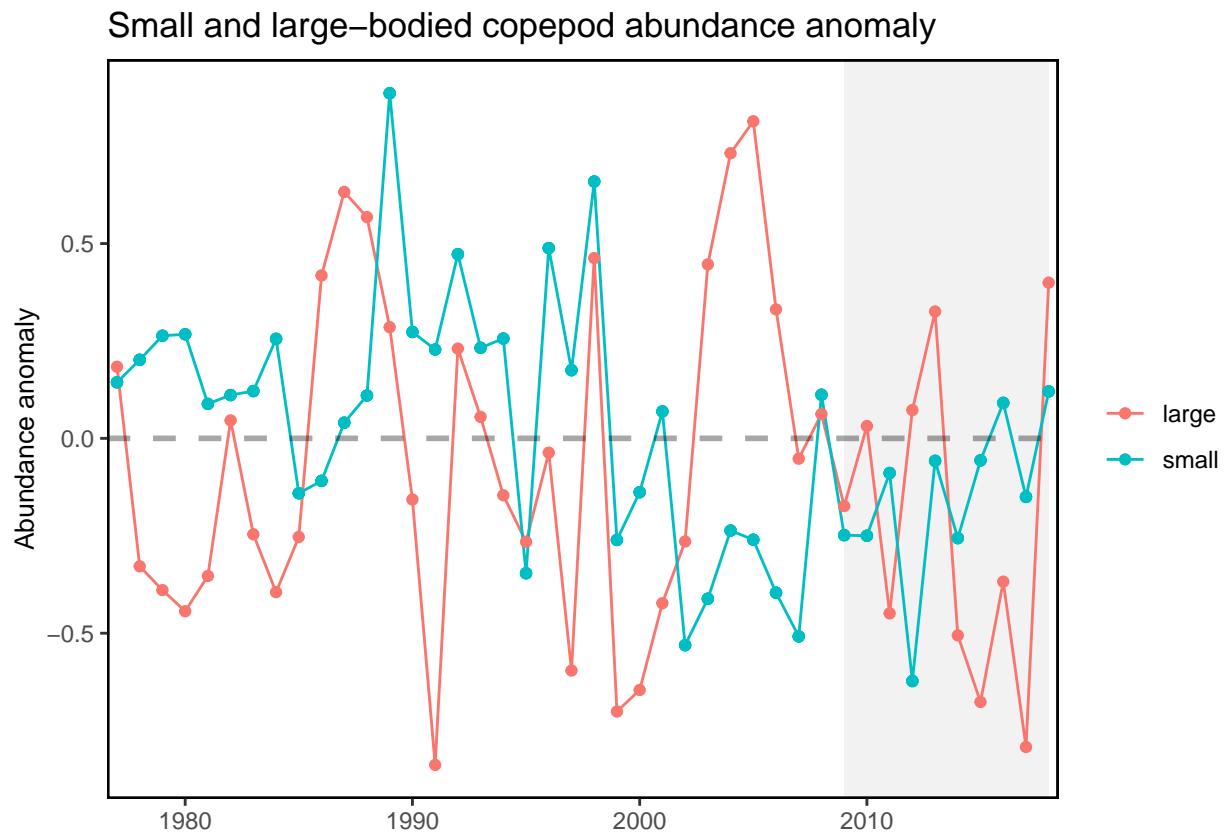


Figure 47.1: Large (red) and small-bodied (blue) copepod abundance in the Mid-Atlantic Bight.

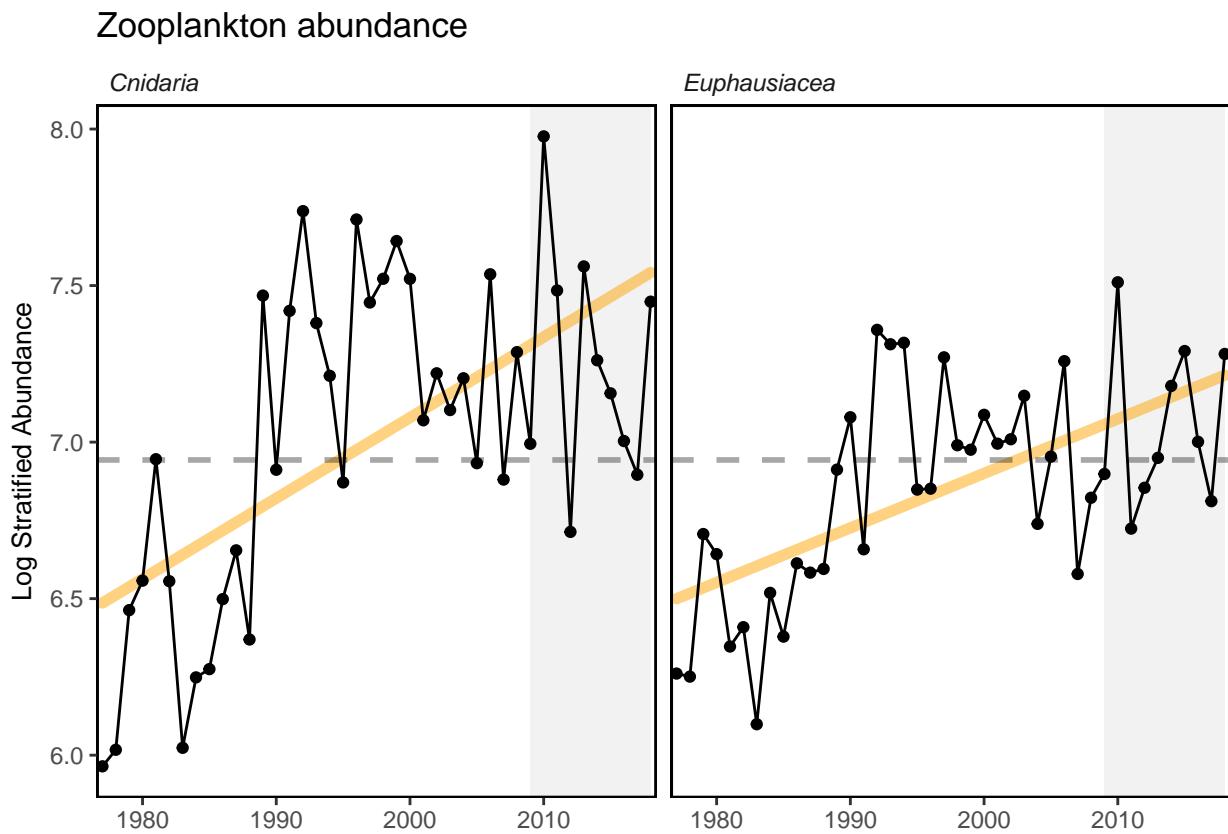


Figure 47.2: Stratified abundance of cnidarians and euphausiids in Mid-Atlantic Bight.

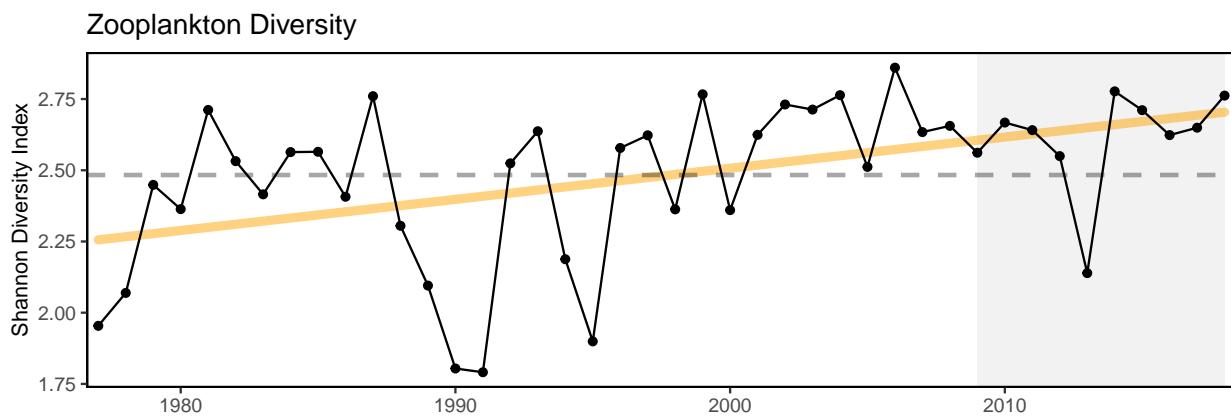


Figure 47.3: Zooplankton diversity in the Mid-Atlantic Bight.

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