*North American Journal of Fisheries Management*, 2025, **45**, 1–17
https://doi.org/10.1093/najfmt/vqae012

**Article**

# A practical guide to economic frontiers for evaluating benefits of multispecies fisheries management

Lauran R. Brewster[1,*], Howard Townsend[2], Jason S. Link[3], Fiona Edwards[1], Geret DePiper[4], Alexander C. Hansell[4], and Steven X. Cadrin[1]

[1]Department of Fisheries Oceanography, School for Marine Science and Technology, University of Massachusetts Dartmouth, New Bedford, Massachusetts, USA
[2]National Oceanic and Atmospheric Administration, National Marine Fisheries Service, Office of Science and Technology, Cooperative Oxford Lab, Oxford, Maryland, USA
[3]National Oceanic and Atmospheric Administration, National Marine Fisheries Service, Office of the Assistant Administrator, Woods Hole, Massachusetts, USA
[4]National Oceanic and Atmospheric Administration, National Marine Fisheries Service, Northeast Fisheries Science Center, Woods Hole, Massachusetts, USA

*Corresponding author: Lauran R. Brewster. Email: lbrewster@umassd.edu.

## ABSTRACT

**Objective**: Management of most fisheries is currently based on single species, so multispecies interactions often constrain fishing, leading to suboptimal yields or overfishing. Ecosystem-based fisheries management (EBFM) uses a more holistic approach to resource access or allocation and takes advantage of multispecies interactions to spread risk and achieve target yields. Portfolio theory is a commonly applied financial tool that considers covariance between assets in an investment portfolio to reduce the risk of achieving economic return targets. This method can be adapted to EBFM for balancing risk with expected benefits for a portfolio of species' revenue. Portfolio management considers species interdependencies (covariance in revenue time series), uncertainty, and sustainability constraints.

**Methods**: We demonstrate how to apply economic frontier analysis using publicly available landings and revenue data from commercial fisheries and calculate the risk gap between historic portfolios and the EBFM frontier to assess past fishery performance. We identify data challenges and offer guidance on practical decisions for applying portfolio analysis to derive annual efficient frontiers (trade-offs between revenue risk and return) and demonstrate the sensitivity of frontiers to these data decisions and model parameters.

**Results**: In accordance with previous portfolio analyses, results show that the multispecies portfolio approach outperformed single-species management and there was forgone revenue for the associated risk taken in the single-species approach.

**Conclusions**: These demonstrations as well as guidance on data and analysis are intended to facilitate broader evaluation and application of multispecies fishery management and portfolio theory to fisheries.

**KEYWORDS:** ecosystem-based fishery management, efficient frontier, portfolio theory, risk management

## LAY SUMMARY

A multispecies portfolio approach outperforms single-species management by reducing risk of forgone revenue or increasing revenue for the same risk level. We provide guidance for developing efficient frontiers.

## INTRODUCTION

Fisheries management has historically been informed by single-species stock assessments with objectives defined by single-species dynamics. Stock assessments incorporate information from the fishery and scientific surveys (if available) to estimate key population trends and management quantities (Hilborn & Walters, 1992). Despite their success at leading to sustainable levels of fishing and rebuilding depleted stocks, they have limitations. These methods rarely incorporate environmental indicators, account for species interactions, or consider socio-economic aspects of the fisheries system. Failure to account for these factors can lead to suboptimal management and yield of fisheries resources (Lynch et al., 2018).

Ecosystem based fisheries management (EBFM) is a more holistic approach that aims to account for interactions within the ecosystem instead of focusing on single species. The concept

**Received:** April 02, 2024. **Revised:** July 31, 2024. **Editorial decision:** October 09, 2024

of EBFM was proposed long ago, but its adoption for management has been slow (Brodziak & Link, 2002; Karp et al., 2023). For example, Lynch et al. (2018) found that in the United States, only 8% of federally managed marine fisheries consider an ecosystem component in assessment or management. The National Oceanic and Atmospheric Administration—the U.S. federal agency responsible for marine fisheries management—has been working on the next generation of stock assessments with a goal of incorporating ecosystem components (Lynch et al., 2018) and has developed a road map to incorporate EBFM (National Marine Fisheries Service [NMFS], 2016). There are a variety of methods to implement EBFM, including frameworks, ecological risk assessments, management strategy evaluation, and ecosystem models (Link et al., 2011; Smith et al., 2007).

Portfolio theory is a potential EBFM tool (DuFour et al., 2015; Yang et al., 2008). Its application to fisheries management is based on methods used in the financial sector, where it has had a profound impact on the field of finance and investment management, providing a systematic framework for understanding risk and return relationships in investment portfolios. Risk is a function of both the variance of each asset and the covariance across assets over time. Portfolio theory is commonly used to manage retirement accounts or long-term investments by diversifying across different asset classes (i.e., stocks and bonds) to reduce overall portfolio risk of achieving target returns (Curtis, 2004). It allows users to quantify alternative risk scenarios and determine an acceptable trade-off between risk and returns. Portfolio users should consider how the value of an individual asset will change in relation to the values of other assets (Baker & Filbeck, 2013). Selecting assets that have low or negative correlation in their value fluctuation can help reduce the risk across the portfolio, given performance targets.

Portfolio management is applicable for EBFM because of similarities between marine systems and the financial sector: fish species are biological assets (i.e., analogous to portfolio assets) that can reproduce and provide economic returns indefinitely (Edwards et al., 2004). A typical management goal is to extract the highest sustainable profit from a fishery. Fisheries often catch multiple species, so fishery managers must consider interactions between species, uncertainty in the system, and sustainability constraints across all species. Returns within a portfolio framework can be any important societal goal (e.g., employment or fish production; DuFour et al., 2015; Edwards et al., 2004), though in practice these goals are often proxied by, for example, commercial revenue or recreational landings due to data constraints. Portfolio theory can be used to quantify time-varying interdependencies among species and their interactions with fisheries as well as to quantify risk (Jin et al., 2016). Because of its applicability to EBFM, several case studies—within the United States and internationally—have conducted fisheries portfolio analysis and documented the benefits of its approach, namely that it can reduce the risk of forgone revenue or increase expected returns (Figure 1; Carmona et al., 2020; Halpern et al., 2011; Jin et al., 2016; Perruso et al., 2005; Radulescu et al., 2010; Sanchirico et al., 2008; Schindler et al., 2010). Consequently, it is of interest to fisheries management bodies, particularly given the precautionary approach often employed in fisheries management.

Despite its promise, it may be challenging for fisheries scientists or managers to conduct portfolio analyses, and we suspect

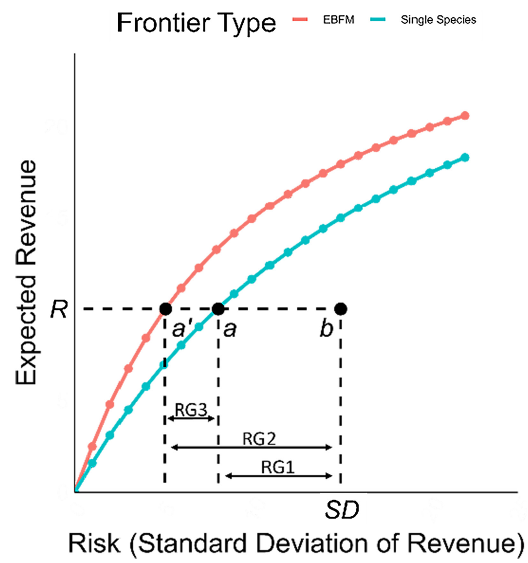


**Figure 1.** Two theoretical efficient frontiers representing single species (blue) and ecosystem-based fisheries management (EBFM; red). The circles on the frontiers indicate various target revenues used to map each frontier; R represents the chosen target revenue; b denotes the observed revenue for the portfolio; a and a′ denote the optimal portfolios on the single-species and EBFM frontiers, respectively; RG1–3 (depicted by the arrows) show three risk gaps as the difference in standard deviation of revenue between b and a, b and a′, or a and a′. Modified from Jin et al. (2016).

this has inhibited uptake. To date, most analyses have been performed by economists and there are no open-source functions or packages to conduct the analyses. Thus, despite the promise of portfolio theory as an EBFM tool, it can be difficult for analysts to conduct unless they have the required expertise.

To facilitate consideration of portfolio theory in fisheries management, we present a practical guide to implementing analysis—combining the methods used in Sanchirico et al. (2008) and Jin et al. (2016)—including recommendations for data preparation and data exploration protocols based upon the lessons we learned and the difficulties we faced while implementing this approach. By minimizing risk over a range of potential revenues, we create efficient frontiers (i.e., a graphical representation of the optimal portfolios that represent the trade-offs between risk and returns; Figure 1) to illustrate the minimal risk achievable for a target revenue given the historical performance of fisheries stock portfolios. Generally speaking, this can be interpreted as maximizing the probability of attaining the target benefits to society. We provide complementary code to conduct portfolio theory and produce data visualizations. Our guide is illustrated using an example time series of publicly available landings and revenue from the northeast United States, and we present several sensitivity analyses to demonstrate the impact of species selection, the time series lengths, information decay factors, and species sustainability parameters used to adapt financial portfolio analysis to fisheries.

## METHODS

Portfolio analysis has several sequential steps: data acquisition; data preparation, including selection of taxa in the portfolio (i.e., portfolio composition); frontier analysis; and visualization for interpreting results. We describe methods in each stage with guidance based on the literature and our experiences (Brewster et al., 2023a, 2023b; Edwards et al., 2004, 2005; Jin et al., 2016).

### Data acquisition

A time series of fishery data by species or other taxonomic group is needed for portfolio analysis, specifically landings and associated value (which in this demonstration is revenue) data. The geographic or organizational scope of data can vary according to the portfolios being considered because portfolio effects (i.e., the spread of risk resulting from selection of assets with differing traits, in this case revenue traits) can be applied to different levels of a fisheries system: an individual fisherman, a local fishing cooperative, a sole-owned fleet, a fishing organization, a fishing port, a coastal state, or a regional fishery management organization. For the purposes of this manuscript, we demonstrate how the portfolio approach can be applied using data downloaded from the publicly available NMFS Landings database (NMFS, Office of Science and Technology, Commercial Landings Query, available at www.fisheries.noaa.gov/foss). These data are assumed to be a census of landings by geographic region, taxa, and fishing sector (commercial and/or recreational), reporting landings biomass, revenue (for commercial landings), and related information. For this example, we focused on commercial fisheries in the New England region and downloaded the full time series (1950–2021) for all taxa. There is also an option to download state specific data.

### Data preparation

All data preparation and analyses were conducted in R 4.2.2 (R Core Team, 2022), and all analyses are available online (https://github.com/lauranbrewster/multispecies_portfolios). The amount of data preparation will vary depending on the case study, but we outline things to look for and steps to be taken for any portfolio composition. For the demonstration, revenue (exvessel value in U.S. dollars) was converted to constant values (i.e., inflation-adjusted to the terminal year of the data set, 2021), using World Bank inflation data (Condylios, 2022). Although landings in metric tons were provided in the data set, these data were rounded to the nearest metric ton, so we converted landings in pounds to metric tons for increased precision.

The data required significant cleansing prior to analyses. We removed data marked "confidential" because no landings or revenue were provided for these species/taxa landing records. The time series had sporadic negative landing values for some taxa in some years and categories of noninterest (e.g., seaweed). Aggregations of multiple species appear in the database when species-specific data were not available and are denoted by "**" in the NMFS name (e.g., "PORGIES**", "MENHADENS**", SKATES, RAJIDAE (FAMILY)**).

### Selection of portfolio assets (i.e., species)

Any group of fish stocks that has technical, biological, market or regulatory interactions is expected to have portfolio effects. Portfolio selection should consider geographic extent (e.g., ecosystems, regional jurisdictions, fishing grounds of mixed-species fisheries) and species with technical interactions (i.e., species caught together), biological interactions (e.g., predators, prey, competitors), market interactions (e.g., common processing or supply chains, product replacement), and management interactions (e.g., available fishing locations or protected areas). It is important that analysts make sure the species compositions are plausible by ensuring that the biological constraints adequately capture both the conservation objectives of fisheries management and realistic stock dynamics.

Species with contrasting trends (i.e., negative covariance in the revenue time series) are needed to minimize risk to the portfolio. The drivers of these correlations do not impact the portfolio analyses or results and could be the result of multiple sources (e.g., technical, market, or ecological interactions). However, understanding the cause of these correlations could help with interpretation of the results. For example, fleets that catch species managed by different fishery management plans or organizations but have negative covariance in temporal productivity could benefit from coordinated management.

Other considerations when selecting the portfolio assets include choosing a period that represents current conditions (e.g., fishery management system, ecosystem state, productivity regime) and data availability for each year because frontier analysis requires consecutive years of revenue and landings data.

To demonstrate portfolio analysis, we arbitrarily selected the top 30 taxa ranked by landings since the beginning of the time series. Landings and revenue of the top 30 taxa varied over time in total magnitude and relative contribution of taxa (Figure S1 [see online Supplementary Material]). Categories that provided little informative value (e.g., VERTEBRATES, JAWED, or WITHHELD FOR CONFIDENTIALITY) that occurred in the top 30 were removed from the portfolio (Figure 2). The NMFS Landings database website states, "Query results with no pounds or dollars shown indicate that landings are present in our database for the selected species but are confidential and have been grouped into WITHHELD FOR CONFIDENTIALITY with other confidential landings in each state." Thus, the "WITHHELD FOR CONFIDENTIALITY" aggregation may comprise some portfolio species but its composition can vary annually.

As previously mentioned, frontier analysis requires consecutive years of value and landings data, so we recommend plotting the time series for each species or species aggregation being considered for the portfolio (Figure 2A). Doing so revealed recent data gaps in our demonstration portfolio that needed to be addressed, particularly for aggregated species, which appear to be being phased out in favor of more species-specific reporting (e.g., PORGIES** not reported since 2008). We found data gaps to be a common occurrence across regions and portfolio compositions and propose five potential solutions for each species with missing data: (1) exclude the taxa from the analysis, (2) aggregate taxa, (3) truncate the time series, (4) interpolate, or (5) add "true zeros" for missing landings. Due to missing observations, we aggregated all squids (i.e., SQUID, LONGFIN LOLIGO, SQUIDS, LOLIGINIDAE**, and SQUID, SHORTFIN ILLEX) into one grouped taxon. SHARK, DOGFISH, SPINY were aggregated with the historic aggregation SHARKS, DOGFISH**. PORGIES** were merged with SCUP. SHRIMPS, PENAEOID** were removed because they are not relevant to the current fishery despite

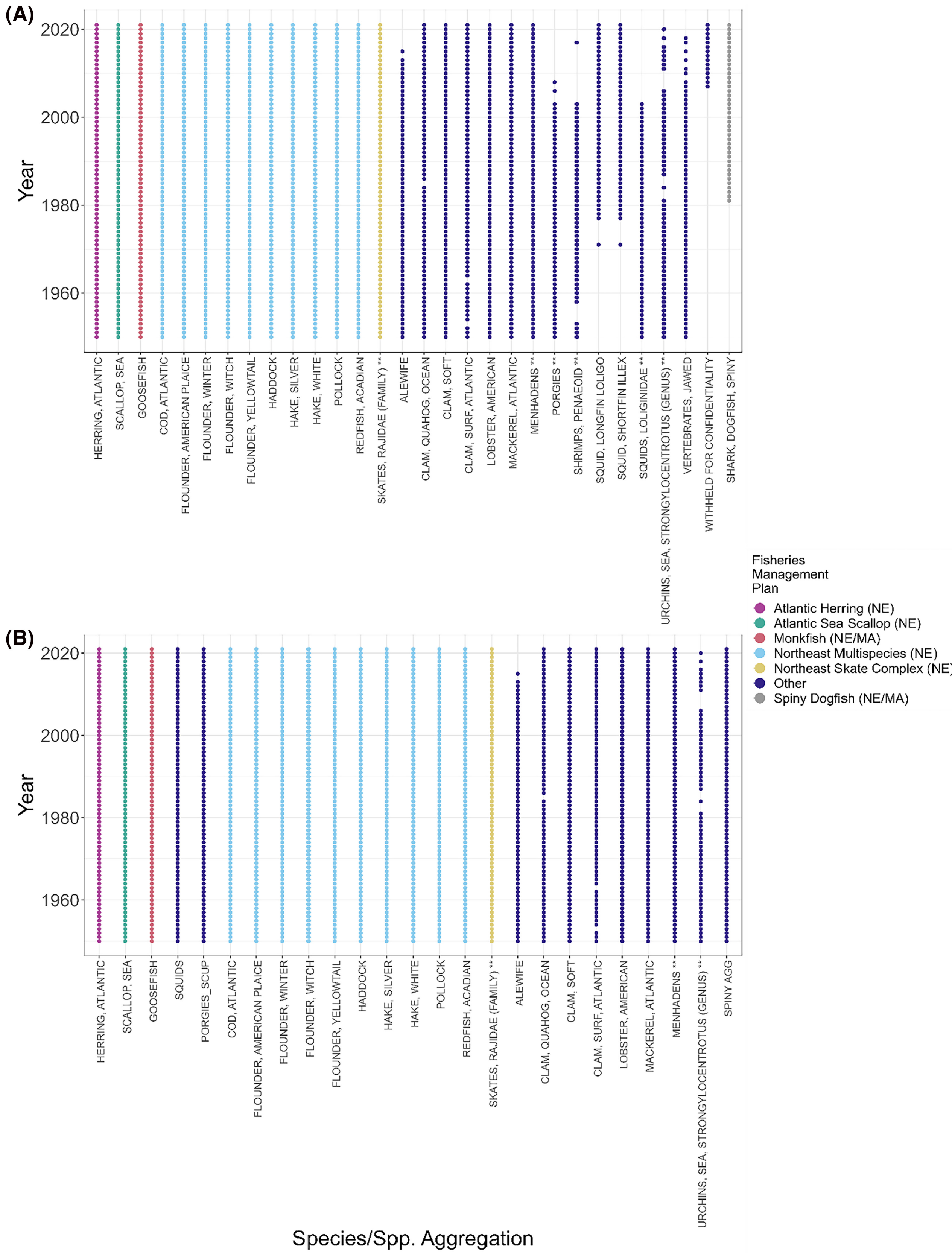


**Figure 2.** (A) Time series of available revenue and landings data for the top 30 new England taxa selected by landings and (B) time series of each portfolio asset after application of missing data solutions (in this case, data aggregation and addition of true zeros where there are gaps). Species/species aggregations are color-coded by their respective fishery management plan; NE = New England, MA = mid-Atlantic. Where species are not currently under management by the New England Fishery Management Council, they were assigned the category "Other."

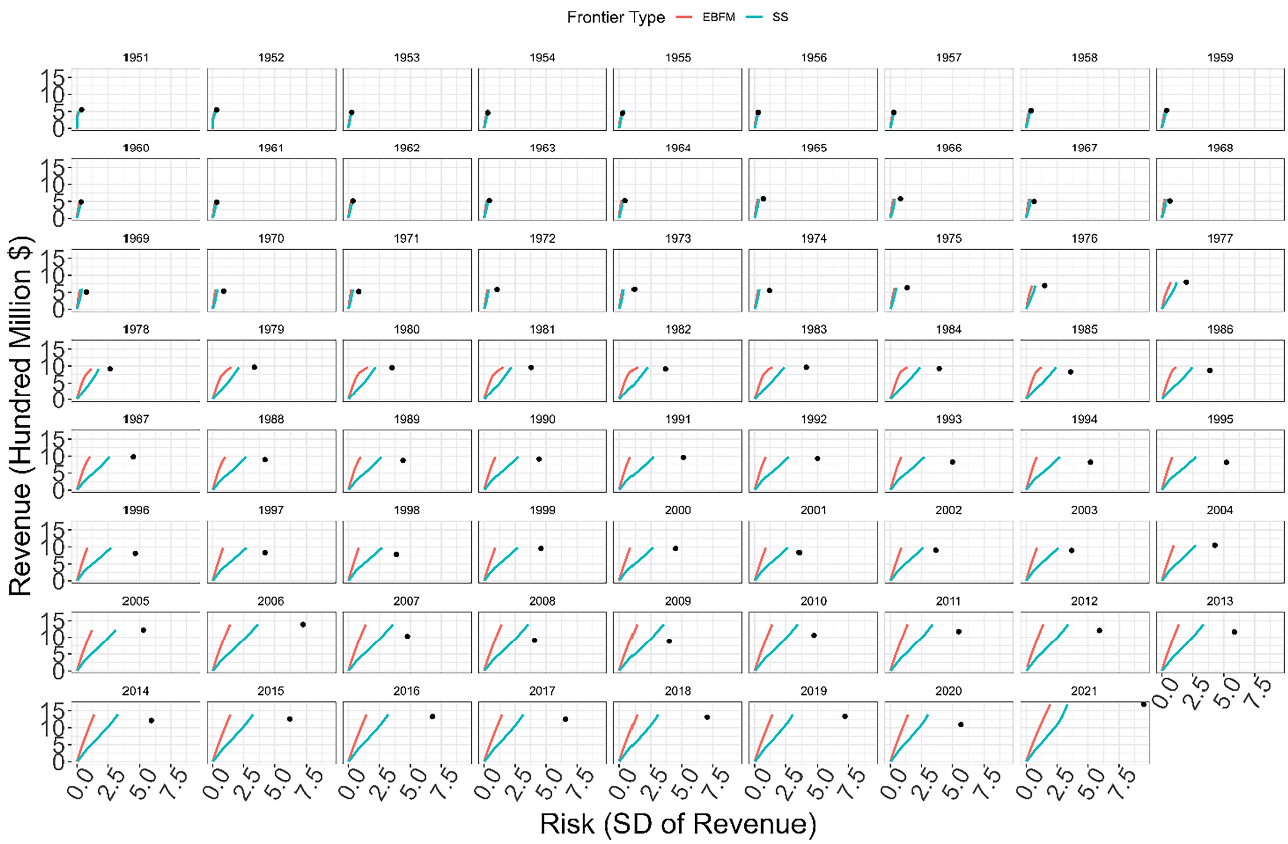


**Figure 3.** Observed revenue (black dot) and ecosystem-based fishery management (EBFM; red line) and single-species management (SS; blue line) efficient frontiers for each year of the time series. The vertical axis depicts the expected revenue (in 2021 dollars) and the horizontal axis depicts risk (measured as standard deviation of revenue). Note: this method of displaying efficient frontiers can incorporate a decay factor to downweight older data and the biological constraint is maximum landings up to year *t*.

apparent historic importance. After considering changes to fishing regulations (e.g., ALEWIFE no longer appears in the public data set after 2015, consistent with the 2015 conservation plan and state moratoria; Figure 2A) and investigating trends in landings, all remaining data gaps were treated as true zeros to produce a time series with consecutive landings and revenue values (Figure 2B). These decisions were supported by understanding of the regional fisheries system, which is necessary for applying the approach for other regions (e.g., Brewster et al., 2023b).

To ensure that we had selected a portfolio composition with a mix of low or negative covariance between species' revenues, we generated a correlation matrix using the "corrplot" package (Wei & Simko, 2024). If most of the revenues are positively or negatively correlated among taxa, an optimization solution may not be possible, and more practically, there would be no reason to use this method, as there are no trade-offs to consider. The example portfolio had a mix of positive and negative correlations (e.g., generally positive correlations among species managed under the Northeast Multispecies Fishery Management Plan), and analysts may use this as a preliminary diagnostic to assess whether a portfolio strategy is likely to generate management gains for the stocks under consideration.

Data preparation and portfolio asset selection for individual case studies can be tailored by amending the Data Preparation.R file provided on GitHub repository. The output from this file can be fed into the subsequent R files to run the frontier analyses.

### Frontier analysis

We use the value-at-risk methodology from the J. P. Morgan RiskMetrics VaR model (J. P. Morgan/Reuters, 1996) to minimize risk (standard deviation of revenue) for desired target revenues. This method assumes that managers are rational actors and consider financial risks (i.e., variability in the value of different fisheries), revenue returns are normally distributed, and future decisions regarding the portfolio are based on risk. We calculated two efficient frontiers: a portfolio frontier representing EBFM that facilitates coordinated management of multispecies portfolios and a single-species frontier that represents a conventional single-species approach to fishery management, accounting for intraspecies variability but not interspecies interactions (Figures 3 and 4).

The frontiers were derived by using a quadratic optimization algorithm to solve Equation 1 (in matrix notation), whereby optimal revenue weights are determined for each species that minimize the risk associated with attaining various target revenues (Figure 1) while accounting for biological constraints. Note that bold typeface indicates a vector or matrix.

$$min_{w_t}\, \boldsymbol{w}_t'\boldsymbol{\Sigma}_t\boldsymbol{w}_t \; s.t.\; \boldsymbol{w}_t'\boldsymbol{\mu}_t \geq R_t,\, w_{i,t} \leq W_{i,t}\; \forall i, \quad (1)$$

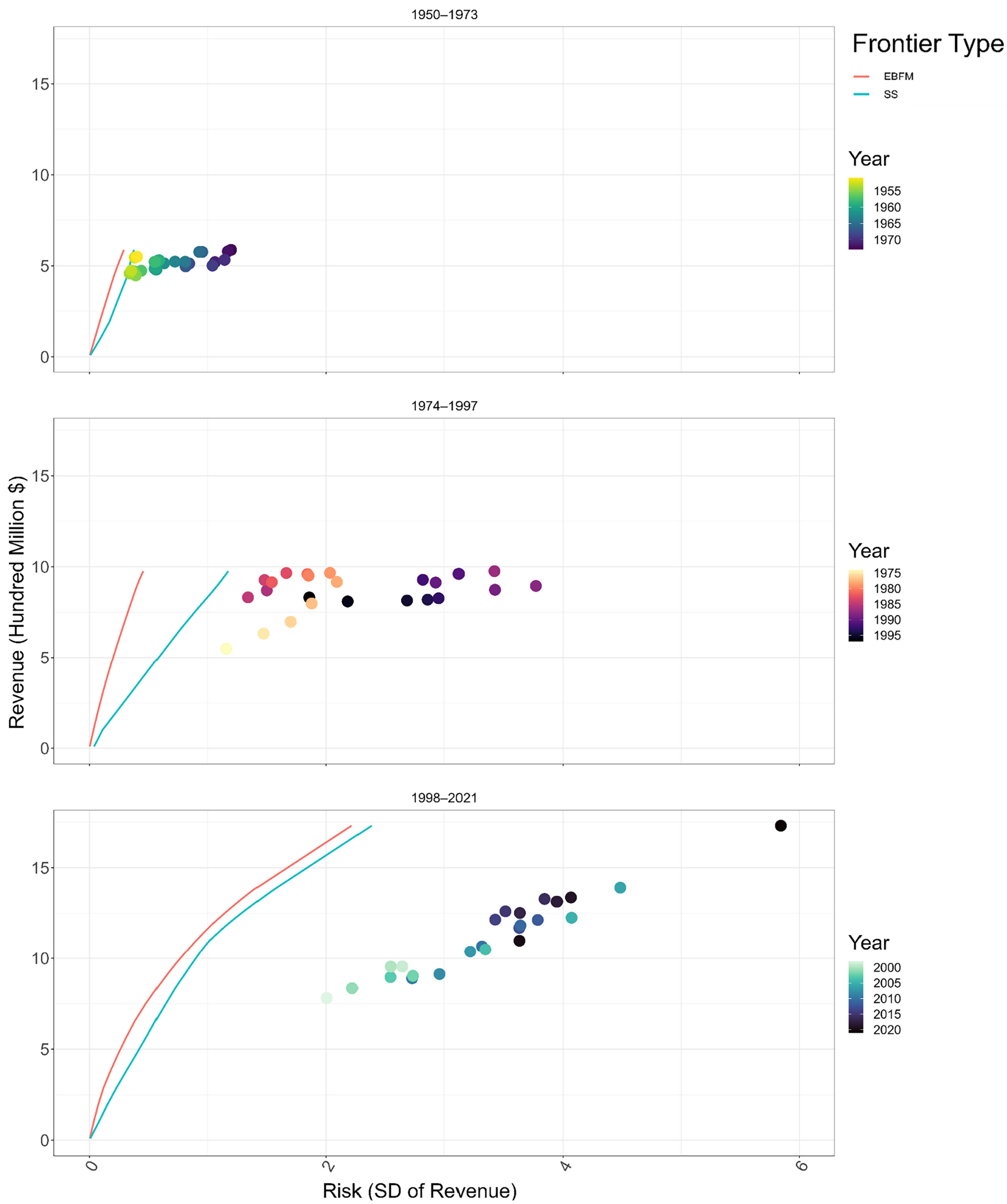


**Figure 4.** Snapshot-style plots where the risk associated with each year of observed revenue (colored dots) is calculated using the covariance matrix for the full time period, matching that which is used to generate the frontier. Thus, to make each frontier (ecosystem-based fisheries management [EBFM], single species [SS]) more applicable when plotted with the observed revenues, the time series was broken into equal durations.

where

$i = 1, \ldots, n$ is the species index

$\boldsymbol{w}_t$ = vector of revenue weights calculated at time $t$. Revenue weights allow fishery managers to select the harvest for each species in the portfolio to minimize risk

$\boldsymbol{\Sigma}_t$ = $n \times n$ covariance matrix at time $t$. For a theoretical single-species management portfolio only the diagonal elements of the covariance matrix were used. Ignoring correlations in species revenues was taken to be analogous to single-species fisheries management where interactions between species are not explicitly considered in decision making

$\boldsymbol{\mu}_t$ = $n \times 1$ vector of expected revenues at time $t$

$R_t$ = target revenue at time $t$

$w_{i,t}$ = a species $i$ element of $\boldsymbol{w}_t$

$W_{i,t}$ = maximum weight for species $i$ at $t$ (i.e., maximum biological constraint/harvest weight)

$\forall i$ = for all species

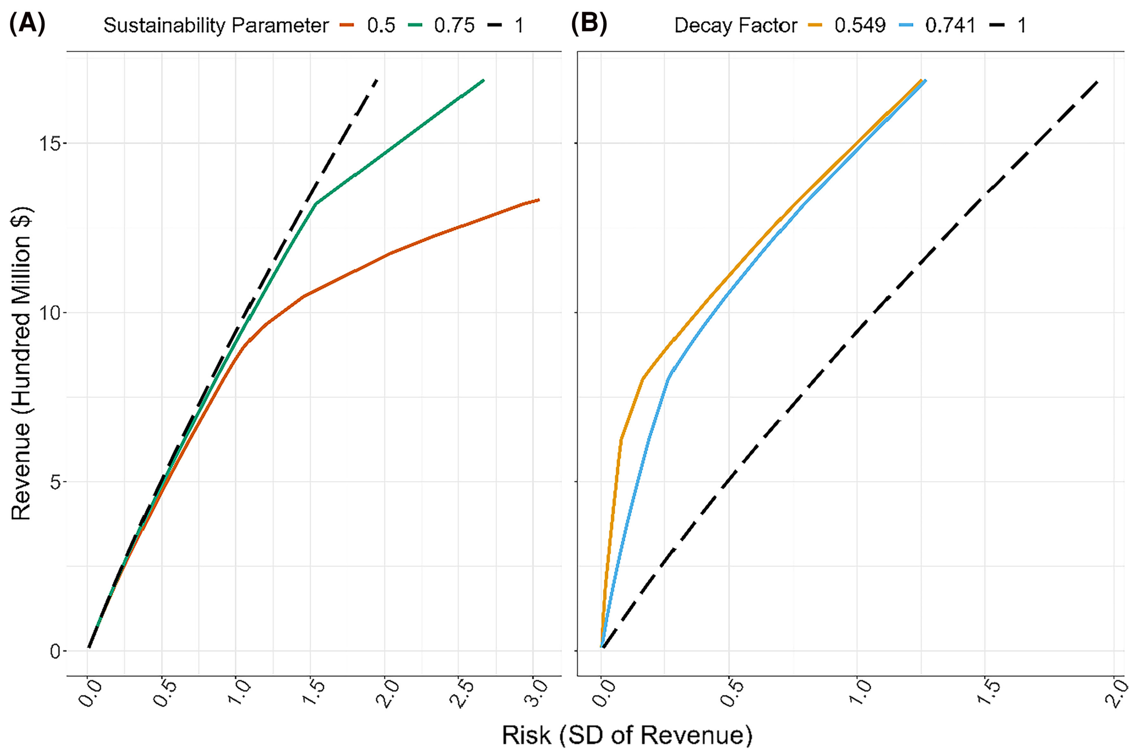


**Figure 5.** Sensitivity of the demonstrated ecosystem-based fisheries management (EBFM) frontier to (A) the sustainability parameter and (B) the decay factor on the 2021 EBFM frontier. The two black dashed lines in both panels represent the EBFM frontier where the sustainability parameter = 1 (i.e., the maximum landing weight obtained during the time series) and the decay factor equals 1 using the full time series (cross-reference the 2021 panel in Figure 3). The colored lines represent the EBFM frontier with a single parameter change. Note the difference in risk scales.

We use a mean-variance representation of expected utility, and thus a quadratic optimizer, due to its applicability across quite general conditions (Meyer, 1987) and its appropriateness in the study region (Jin et al., 2016). However, alternative specifications accounting for important higher moments of the distribution can, and should, be employed where necessary. For example, nonnormality of returns could indicate the need to select a value function that better accounts for the skewness or kurtosis of the distribution. We applied methods used in the finance sector to fisheries stocks portfolios, so adjustments to the VaR finance model are necessary to account for ecological and policy constraints and variability of fisheries stocks. Minimum and maximum revenue weights should be set to reasonable values based on historical patterns in revenues and policy constraints. For example, allowing the minimum revenue weight ($w_{i,t}$) of a stock to be zero would be equivalent to allowing the fishery for that species to be closed. In finance, a buyer can borrow money to buy shares of an asset (stock, bond, etc.) such that revenue weights derived from optimization can exceed historic weights. An analogous increase in revenue weights for harvest fisheries species may not be sustainable, particularly for stocks with a long exploitation history, so a sustainability parameter is used to limit the maximum revenue weights in the optimization as part of the biological constraint. Common practice has been to use a single parameter for the sustainability constraints. In this paper and others (Carmona et al., 2020; Sanchirico et al., 2008), sustainability has been a proportion of the maximum catch. This may be a conservative approach (particularly for some species that have been underexploited throughout the time series) but is appropriate for demonstration and for early stages of applying portfolio analysis to management. Alternative sustainability constraints could be based on factors that affect ecosystem productivity and fisheries landings (e.g., estimates of maximum economic yield from bioeconomic models that account for ecological, biological, economic, and management factors influencing stock productivity).

Finally, external conditions influencing fishery production that existed in the past (e.g., climate, markets) may have changed, in which case past revenues in a portfolio should be downweighted for the optimization (i.e., using a decay factor). The decay factor serves to minimize the importance of past years' revenues in the mean-variance optimization used to generate the efficient frontier (Figure 5). The application and magnitude of a decay factor is dependent on the period of the analysis, the time step of the data, and factors that may have influenced fishing revenues. For example, if the analysis is being conducted on a portfolio of fish stocks for a period of a few years with monthly revenue data, then all data in the analysis may represent current conditions and a decay rate need not be applied (i.e., $\lambda = 1$). For this demonstration, we used an annual time step, as that was the shortest available when using the NMFS Landings database. In such cases, the environmental conditions and management plans that allowed for catch experienced in early years may likely not exist in later years. Thus, when generating frontiers that may be used to guide management, the influence of early years on the optimization should be downweighted to prevent optimal results that cannot be achieved under current conditions. Other authors (e.g., Jin et al., 2016; Radulescu et al., 2010; Sanchirico et al., 2008) noted that exponential smoothing is one approach for handling external variability in conditions that influence productivity and other options should be considered such as autoregressive models of expected revenues. Jin et al. (2016) note that "Multiple drivers affecting the covariance matrix include ecological (food web trophic interactions), biological (fish stocks), and economic (market prices) effects, fishing operations and technologies (bycatch), and management (input and output controls, area management, etc.)." For increased realism, some of these factors could be incorporated into bioeconomic models and used to generate efficient frontiers. These models could also be used to project future conditions and likely changes in efficient frontiers (e.g., as fisheries production is influenced by climate). For this demonstration and for initial application of this approach to management, using exponential smoothing provides a conservative estimate of efficiency frontiers.

*Step one*

Set the parameters, including:

1. the biological constraints (i.e., minimum, and maximum harvest weights to constrain the revenue weights for each species at time $t$; Equation 2). Setting the minimum weights to zero allows the optimization algorithm to find solutions where some stocks may not be harvested. For other management applications, the minimum weight could be set higher if a fishery closure is not feasible. A sustainability parameter ($\gamma$) can be used in setting the maximum weight for species $i$ at $t$. We set $\gamma = 1$. If set to one, the optimization algorithm can find solutions where stocks may be harvested at their highest historical levels. For other management applications, this parameter could be lowered by the analyst/fisheries management to control harvest.
2. The decay factor ($\lambda$) to downweight earlier data in the time series. If the system is rapidly changing and only the most recent years represent current conditions, then a greater decay rate should be applied. By contrast, if the system is relatively stationary, decay rates may not be needed to represent current conditions. If $\lambda = 0.549$, 5% of these data remain after 5 years; if $\lambda = 0.741$, 5% of these data remain after 10 years. If $\lambda = 1$, all data are given equal weight. We set $\lambda = 1$ for demonstration but recommend that the analyst set the decay rate according to the length of the time series and historic conditions relating to the portfolio assets. Note that the decay factor will impact the model's "burn-in" period (Figure 3).

Estimated frontiers are somewhat sensitive to changes in these parameters, so sensitivity analyses can be conducted to see the impact of some of these decisions on the frontiers (Figure 5). Lowering the sustainability parameter will reduce the attainable revenue for a given risk (Figure 5A), and an increased decay rate will result in a frontier that better reflects current conditions (Figure 5B).

For our demonstration, minimum harvest weights were set to zero. Maximum harvest weights ($W_{i,t}$) were set as the maximum annual harvest for each species attained between the beginning of the time series until time $t$:

$$W_{i,t} = \frac{\gamma_{i,t} B_{i,t}}{\Omega_{i,t}}, \tag{2}$$

where

$$\Omega_{i,t} = \frac{\sum_{k=1}^{t} \lambda^{t-k+1} p_{i,k} y_{i,k}}{\sum_{k=1}^{t} \lambda^{t-k+1} p_{i,k}} \tag{3}$$

$\gamma_{i,t}$ = the sustainability parameter for species $i$ at time $t$
$B_{i,t}$ = maximum sustainable catch specified as the maximum catch up until time $t$ for each species
$\Omega_{i,t}$ = weighted average catch over time (including decay) for species $i$ at time $t$
$\lambda$ = decay factor
$p_{i,k}$ = price of species $i$ at time $k$
$y_{i,k}$ = catch quantity

The impact of the decay factor on the frontier depends on the trend in revenue. In this instance, where revenue increases throughout the time series (Figure S1), a lower decay factor (i.e., 0.549) results in a frontier where more revenue can be attained for a given risk level than when $\lambda = 1$. Conversely, applying a lower decay factor to a portfolio with a decreasing revenue trend throughout time would result in a frontier where less revenue can be attained for a given risk level.

*Step two*

Calculate the covariance matrix of revenue.

Each element of the covariance matrix $\Sigma_{i,j,t}$ is calculated as the covariance of revenue between species $i$ and $j$ (or variance if species $i = j$) at time $t$ (Equations 4 and 5). The decay factor, $\lambda$, is incorporated into each element (Equation 4).

$$\Sigma_{i,j,t} = \frac{\sum_{k=1}^{t} \lambda^{t-k+1} \left(r_{i,k} - \mu_{i,t}\right)\left(r_{j,k} - \mu_{j,t}\right)}{\sum_{k=1}^{t} \lambda^{t-k+1}}, \tag{4}$$

where

$$\mu_{i,t} = \frac{\sum_{k=1}^{t} \lambda^{t-k+1} r_{i,k}}{\sum_{k=1}^{t} \lambda^{t-k+1}} \tag{5}$$

$r_{i,k}$ = revenue of species $i$ at time $k$
$\mu_{i,t}$ = expected revenue of species $i$ at time $t$ (an element of $\boldsymbol{\mu}_t$; Equation 1).

*Step three*

Select the target revenues from which to generate the frontier. We generated 20 targets across the distribution of total annual revenues (i.e., revenues corresponding to the 0th, 5th, 10th, …, 95th, 100th percentile) from the beginning of the time series up until time $t$. We also ensured that the annual revenue for time $t$ was included as a target for calculating the risk gap (see Frontier analysis, step 5) and provided a sequence of values between zero and the value at the 0th percentile to generate full frontiers that start with zero revenue and risk. These target revenues can be changed within the function script provided on GitHub.

*Step four*

Use a quadratic optimization algorithm to solve Equation 1 for each target revenue and each frontier type:

1. The portfolio frontier is calculated using the full covariance matrix.
2. The species frontier is calculated using the diagonal of the covariance matrix (Sanchirico et al., 2008).

To solve Equation 1, we used the ipop quadratic programming solver from the "kernlab" package (Karatzoglou et al., 2024; based on the LOQO software [Vanderbei, 1999]). This requires setting convergence tolerances ("margins" in the ipop function) to determine how close the solution gets to the constraints. The analyst should consider the order of magnitude of the revenue when doing this. If the tolerances are too low, the algorithm may have difficulty finding a solution. If the tolerances are too large, the solutions might not be meaningful. For example, if a portfolio revenue is \$1 million and the tolerances are \$1,000, then the effective revenue is \$1 million ± \$1,000. Derived quantities (like the risk gap) should be greater than \$1,000 to be meaningful rather than a function of the tolerance. For this demonstration, we set tolerances to within \$1,000 of the target revenue.

The solution of the quadratic optimizer provides an optimal revenue weight for each taxon ($\hat{w}_{i,t}$) in the portfolio—within the constraints provided—that minimizes the risk associated with achieving each target revenue in the frontier (Figure 1). The optimal revenue weights are used to calculate taxon-specific landings, calculated as

$$\hat{w}_{i,t}\Omega_{i,t} \tag{6}$$

and taxon-specific optimal revenue ($\hat{r}$; which when summed for all taxa equals $R_t$):

$$\hat{r}_{i,t} = \hat{w}_{i,t}\mu_{i,t}. \tag{7}$$

The risk (as standard deviation of revenue) associated with each target revenue is calculated using the vector of optimal weights ($\hat{\boldsymbol{w}}_t$) and the covariance matrix:

$$\sqrt{\hat{\boldsymbol{w}}_t' \boldsymbol{\Sigma}_t \hat{\boldsymbol{w}}_t} \tag{8}$$

After the minimized risk associated with each target revenue has been calculated, the frontier curves can be plotted. Using many target revenues in the optimization loop enables the analyst to produce a smoother portfolio. However, independent optimizations at multiple target revenues increase the chance that solutions will be singular. If the optimization algorithm is not able to find the solution and it impedes frontier construction, an analyst can consider adjusting the composition of the portfolio, changing the revenue scale, time series, or number of targets in the optimization loop or increasing the tolerances. We encountered convergence issues for some portfolio configurations, input parameters, and optimization constraints. In such instances, we skipped target revenues that had singular solutions (using the tryCatch function in base R) and moved on to the next so that it did not impede our ability to generate appropriate frontiers. After portfolio selection and prior to running the frontier analysis, revenue values should be scaled. Doing so changes the order of magnitude of the variables and constraints to be more favorable for computation. In this demonstration, we scaled all our values between 0 and 1 by dividing by the largest species/taxon maximum annual revenue (i.e., \$921,391,217, LOBSTER, AMERICAN in 2021; Figure S1). Thus, after optimization, these values should be rescaled to their original magnitude.

*Step five*

Calculate the risk taken to achieve the observed revenue using the vector of implicit revenue weights ($\tilde{\boldsymbol{w}}_t$) and the covariance matrix. This equates to point "b" in Figure 1 and is calculated as

$$\sqrt{\tilde{\boldsymbol{w}}_t' \boldsymbol{\Sigma}_t \tilde{\boldsymbol{w}}_t}, \tag{9}$$

where implicit weights are calculated as

$$\tilde{w}_{i,t} = \frac{r_{i,t}}{\mu_{i,t}}. \tag{10}$$

*Step six*

Determine risk gaps. Several risk gaps (measures of excessive risk-taking; Figures 1 and 6) can be calculated as the difference in risk between

1. the observed revenue and the same revenue on the single-species frontier (Figure 1, point a; Equation 11), which represents the reduction in risk between opportunistic fishing without consideration of within species variation in revenue versus accounting for optimized within-species revenue (Carmona et al., 2020; risk gap one);
2. the observed revenue and the same revenue on the portfolio frontier (Figure 1, point a′; Equation 11) which represents the risk reduction that could have been achieved by implementing the EBFM approach (Jin et al., 2016; risk gap two); and
3. the two frontiers, which demonstrates the value of accounting for species interactions and quantifies the improvement of using a portfolio approach over an optimized single-species approach (Carmona et al., 2020; risk gap three).

We calculated the risk gaps at the realized revenue value for each year of the time series:

$$g_t = \frac{\sqrt{\tilde{\boldsymbol{w}}_t' \boldsymbol{\Sigma}_t \tilde{\boldsymbol{w}}_t} - \sqrt{\hat{\boldsymbol{w}}_t' \boldsymbol{\Sigma}_t \hat{\boldsymbol{w}}_t}}{\tilde{\boldsymbol{w}}_t' \boldsymbol{\mu}_t}, \tag{11}$$

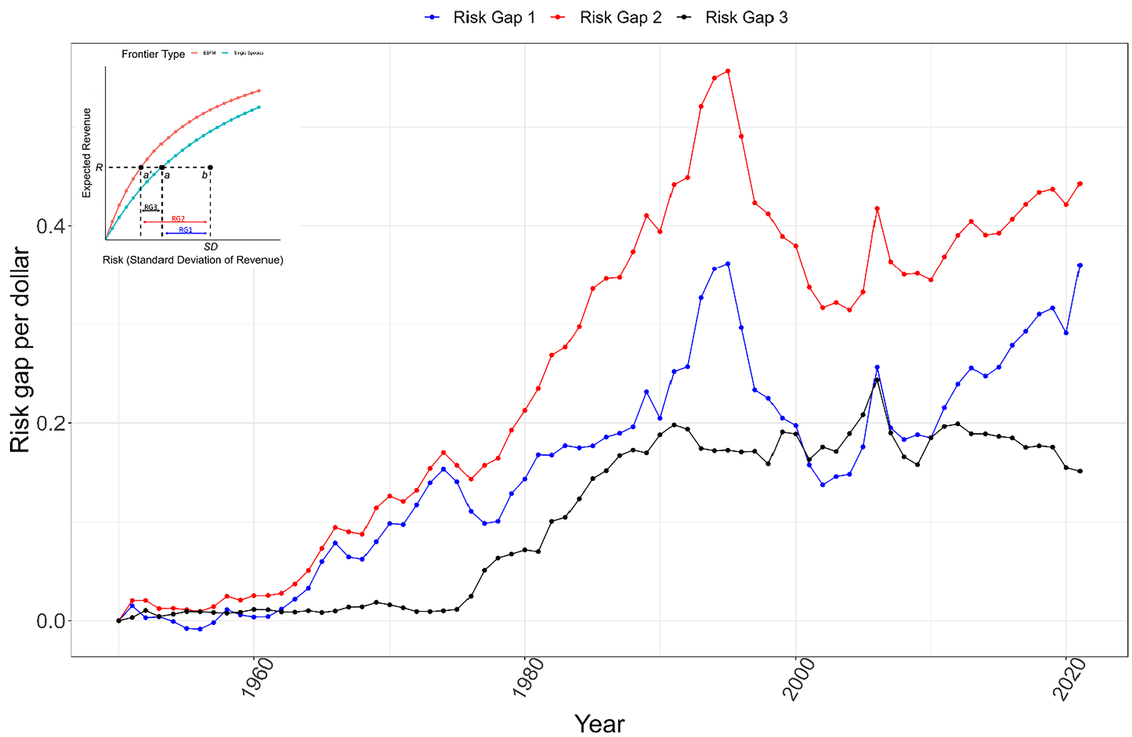


**Figure 6.** Time series of the three risk gaps per dollar of revenue (i.e., they are normalized), presented in Figure 1/insert. Risk gap one is the difference in risk taken to achieve the realized revenue (point b) versus the minimized risk that would have been assumed using the single-species approach. Risk gap two represents the difference in risk between the realized revenue versus using the portfolio approach. Risk gap three shows the difference in risk between the two frontiers at the observed revenue amount for any given year.

where $\tilde{\boldsymbol{w}}_t$ is the vector of implicit revenue weights that were chosen to obtain the observed revenue and $\hat{\boldsymbol{w}}_t$ is the vector of optimal revenue weights estimated by the quadratic optimizer (for either the single-species or EBFM frontier) to achieve the target revenue $R_t = \tilde{\boldsymbol{w}}_t'\boldsymbol{\mu}_t$. To calculate risk gap three, the implicit weights in Equation 11 are replaced with the optimal weights from the single-species frontier. All risk gaps can be expressed as an absolute or relative risk (per dollar) value through the exclusion/inclusion of the denominator (Figure S2) in Equation 11.

### *Step seven*

Visualize the results. Two methods have been used to visualize the frontiers in relation to the annual observed revenues. Sanchirico et al. (2008) presented a "snapshot" style plot (that does not include a decay factor i.e., $\lambda = 1$) that simultaneously depicts all observed revenues against the frontier for the entire time series and where the frontiers are calculated using a biological constraint equal to the maximum catch throughout the time series (Figure 4). Jin et al. (2016) presented a multi-panel plot that shows how the frontier updates with the integration of each additional year (Figure 3) and adjusts the biological constraints so that it is equal to the maximum catch up until time $t$. Each has strengths and limitations. The snapshot style plot, while providing a simple visual aid, can be misleading, particularly when generated from a lengthy time series. The frontier is generated using target revenues and a covariance matrix calculated from the full time series, and so for direct comparison, the risk associated with each annual observed revenue should be calculated using the same covariance matrix (Figure S3). However, that may not reflect the risk that was assumed in earlier years because the constraints may have changed. This can be partially overcome by splitting the time series into chunks, with breakpoints based on catch composition (as in Sanchirico et al., 2008), management regime shifts, and so forth (see Conduct sensitivity analyses). Alternatively, it may be more appropriate to calculate the risk using the covariance matrix up until time $t$ (as is done in the multi-panel plot), but this does not allow for direct comparison with the full-time-series single frontier (Figure S3). Thus, the multi-panel plot shows a more direct comparison of frontiers and observed revenue through time (and thus a more appropriate risk gap) but is arguably harder to digest.

Frontier results need to be considered in the context of constraints. For example, some observed revenues may occur above the frontier, suggesting that more revenue could have been achieved for the same risk, which appears to violate financial portfolio theory. Further, some observed revenues assume risk that extends beyond where the frontiers end, thus not producing a portfolio revenue value for that level of risk. Both situations occur because of the biological constraint parameter, which affects the frontier but not the observed revenue and associated risk (Carmona et al., 2020; Jin et al., 2016). Alternatively, an observed revenue occurring above the frontier could be the result of the tolerance of the optimization, which may need to be reduced. Finally, if the portfolio primarily comprises species with strong positive correlations, the single-species frontier could potentially outperform (i.e., be situated to the left and above) the portfolio frontier (Sanchirico et al., 2008). This is

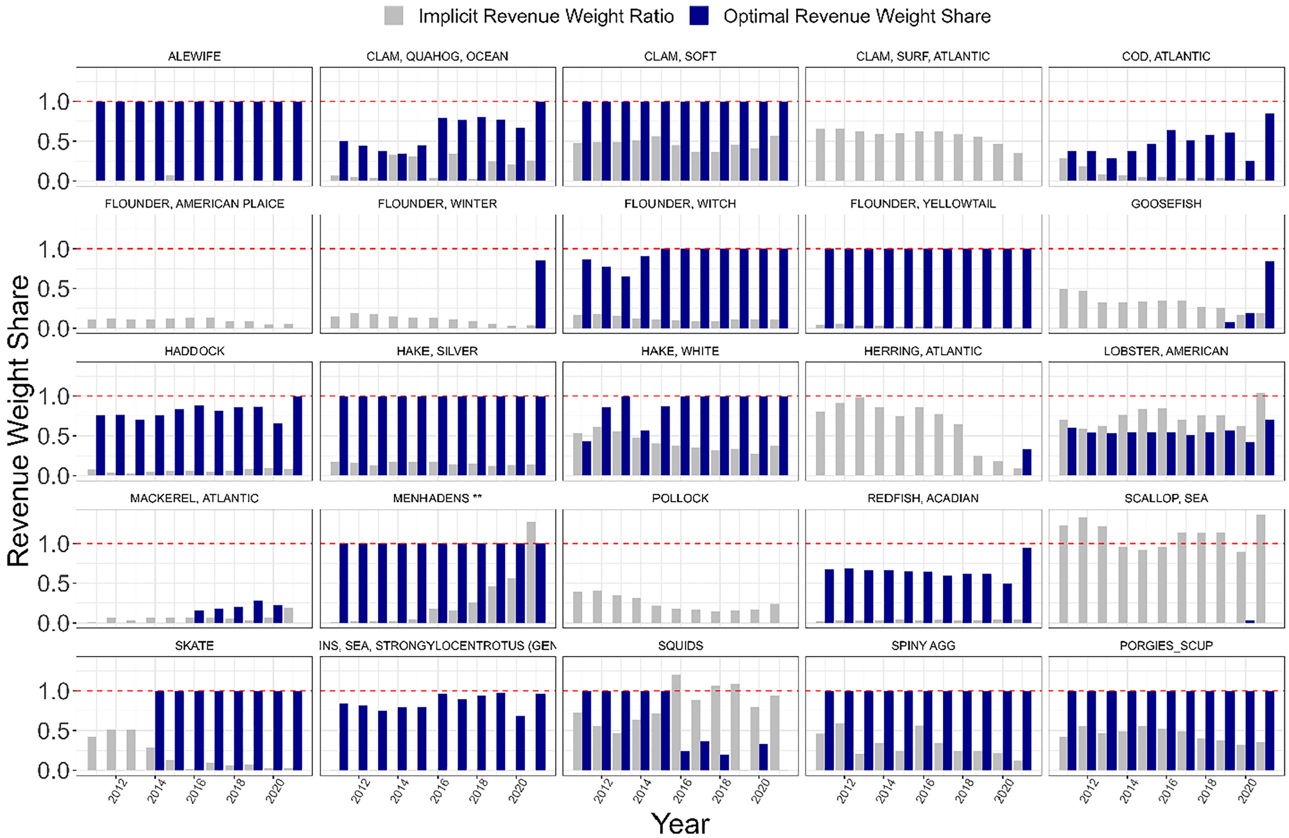


**Figure 7.** Implicit revenue weight ratio (gray) for each species/taxa and optimal (blue) revenue weight shares calculated as target return = annual observed revenue. For ease of visualization only the last 10 years of the time series are shown. Comparison of optimal versus implicit weights provides insight into how the observed revenue was achieved versus how it could have performed if it operated on the ecosystem-based fisheries management frontier. The red dashed line represents the maximum revenue weight share, limited by the biological constraint. Thus, if the implicit revenue weight ratio exceeds one, the species/taxa was fished above the maximum amount.

because the actual risk is not assessed fully by the single-species frontier (i.e., in this case, the risk would have a downward bias when assessed using only the diagonal of the covariance matrix).

To achieve target revenue at lower risk as suggested by the EBFM frontier, fishery managers need to know what quantity of each species/taxa contributes to the target revenue with minimized risk (i.e., the optimal revenue weight share for each taxa). Revenue weight shares (0–1) are calculated for a target revenue as

$$\frac{w_{i,t}}{W_{i,t}} \tag{12}$$

If a taxa's revenue weight share is zero, it should not be landed, whereas if it equals one, that taxa should be harvested at its maximum harvest rate (i.e., at the biological constraint) to achieve the target revenue with minimized risk (Figure 7). We can assess past performance by comparing optimal and implicit revenue weight shares for each taxon for a given revenue (Figure 7).

In plotting the risk gaps, frontiers, and optimal and implicit weights, we can see how management might benefit from the portfolio approach. In this demonstration, for the terminal year of the time series (2021), more risk was taken to achieve the target revenue than was necessary, had the portfolio approach been implemented (Figures 3, 4 and 6). This is due to a mismatch between the implicit weights (i.e., how much of each asset was landed) and the optimal weights (i.e., what should have been landed to minimize risk) for that year. For example, the optimal weights (calculated using Equation 6) suggest that landings should have been higher for Yellowtail Flounder *Myzopsetta ferruginea* (formerly known as *Limanda ferruginea*), Atlantic Cod *Gadus morhua*, and Haddock *Melanogrammus aeglefinus*, with less emphasis on sea scallops *Placopecten magellanicus* (Figure 7). Risk gaps generally increased from 1950 to a peak in the mid-1990s, then generally decreased (Figure 6). The peak suggests that the benefits of portfolio management would have been greatest when many stocks in the region were relatively depleted. In 1996, there was a substantial revision to the management system that required new regulatory conditions for most fisheries in the region to end overfishing and rebuild depleted stocks (Rosenberg et al., 2006). In the more recent period, there was a minor peak in risk gaps in 2006 that perhaps resulted from a spike in herring prices, driven by a change in perception of stock size (Shepherd et al., 2009), a decrease in allowable catch, and a demand for herring bait. These interpretations demonstrate how examination of input data and considering

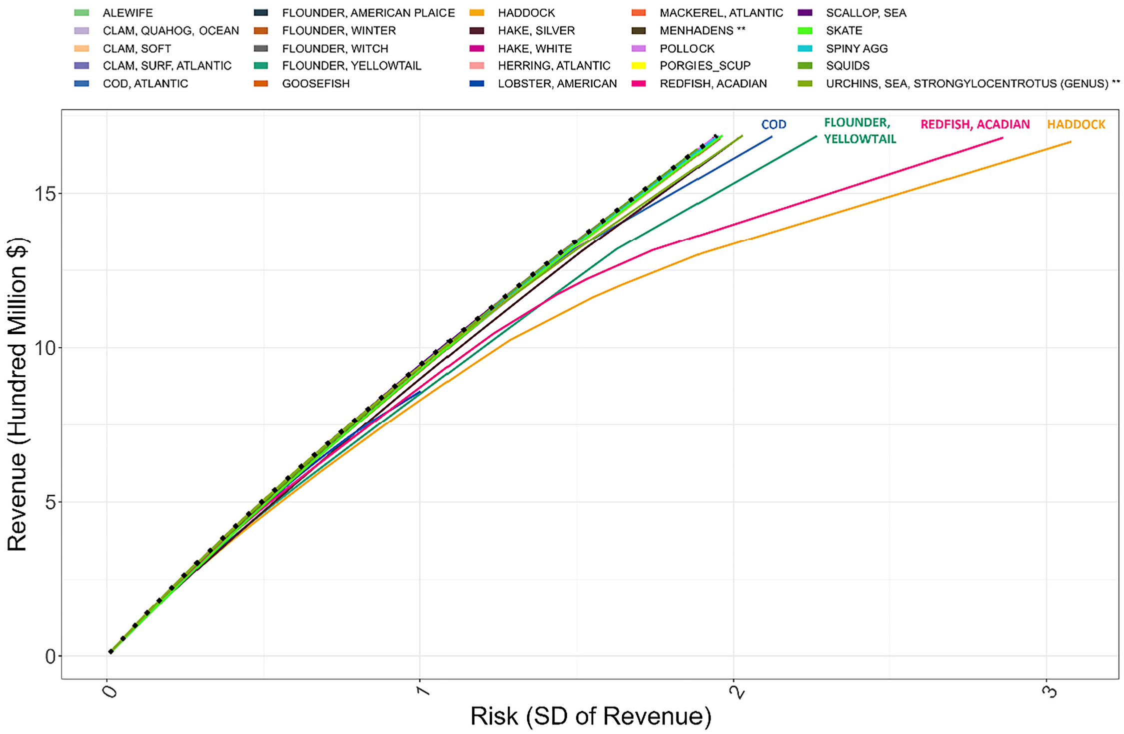


**Figure 8.** Sensitivity to portfolio species configuration using the full time series and a decay factor and sustainability parameter = 1. The black dotted line represents the frontier derived from the full portfolio. Each colored line represents the frontier derived from the full portfolio minus the species indicated by the frontier color. The portfolio with American lobster removed attains much lower revenue, while the portfolio with Haddock removed results in increased risk.

regional fishery conditions can help to understand results of frontier analysis.

### Conduct sensitivity analyses

The frontier results are sensitive to data decisions (taxa in the portfolio, time series) and optimization constraints, which can give different information to inform fishery management. The primary species in a portfolio will typically be defined by managers or fishery stakeholders. However, there will be trade-off decisions on which minor or secondary species to include because minor species may not have a continuous revenue series or may have inconsistent taxonomic aggregations. Frontiers—and thus risk gaps—may be sensitive to decisions to include or exclude minor species. Thus, we recommend conducting sensitivity analyses to assess the influence of individual species on the portfolio. This is also beneficial for the analyst and fishery managers by helping to provide context as to which species are economically important to the portfolio or increase risk. For example, we performed leave-one-out sensitivity analysis with the demonstrated top 30 portfolio. Here, when using the full time series, removing American lobster *Homarus americanus* or sea scallop (Figures 8 and S4) from the portfolio substantially reduced potential revenue while maintaining similar risk exposure. Conversely, removing Haddock, Acadian Redfish *Sebastes fasciatus*, and Yellowtail Flounder did not greatly reduce attainable revenue but does increase associated risk. These three species (along with Silver Hake *Merluccius bilinearis* and Alewife *Alosa pseudoharengus*) represented much of the negative covariance in the portfolio, likely because they were targeted using different gear to the rest of the northeast multispecies fishery species. Yellowtail Flounder were targeted with a flatfish net (e.g., cookie sweep, low headrope); Haddock are more off-bottom and often targeted with a separator or Rhule trawl; and Acadian Redfish, which occupy deeper waters, are fished with slightly smaller mesh.

We also recommend conducting sensitivity analysis to determine the impact of the time series on the portfolio frontier. Analysts should consult local experts or literature to help determine break points in the portfolio based on market conditions, regime shifts, or management changes and conduct sensitivity analysis within that time frame. Additionally, sensitivity analyses can be conducted between time series that reflect, for example, different management regimes to assess the impact of regime shifts on the economic performance of fisheries.

Sensitivity analysis of the demonstrated portfolio frontier to the time series selection showed considerable differences in the risk assumed to achieve target revenues (Figure 9). We used the most recent data in all sensitivity analyses because of the increasing trend in revenue (Figure S1), so the maximum attainable revenue was the same between frontiers. However, for a constant revenue target, the time series length has a substantial impact on calculated risk levels; using the full time series, more risk was taken to attain all but the highest revenue values. Conversely, the risk–reward trade-off was smallest when basing the analysis on data collected since 1980. The position of the more recent frontiers (above and to the left of the full-time-series frontier) reflects those generated using a decay factor, where older data in the time series are downweighed (Figure 5).

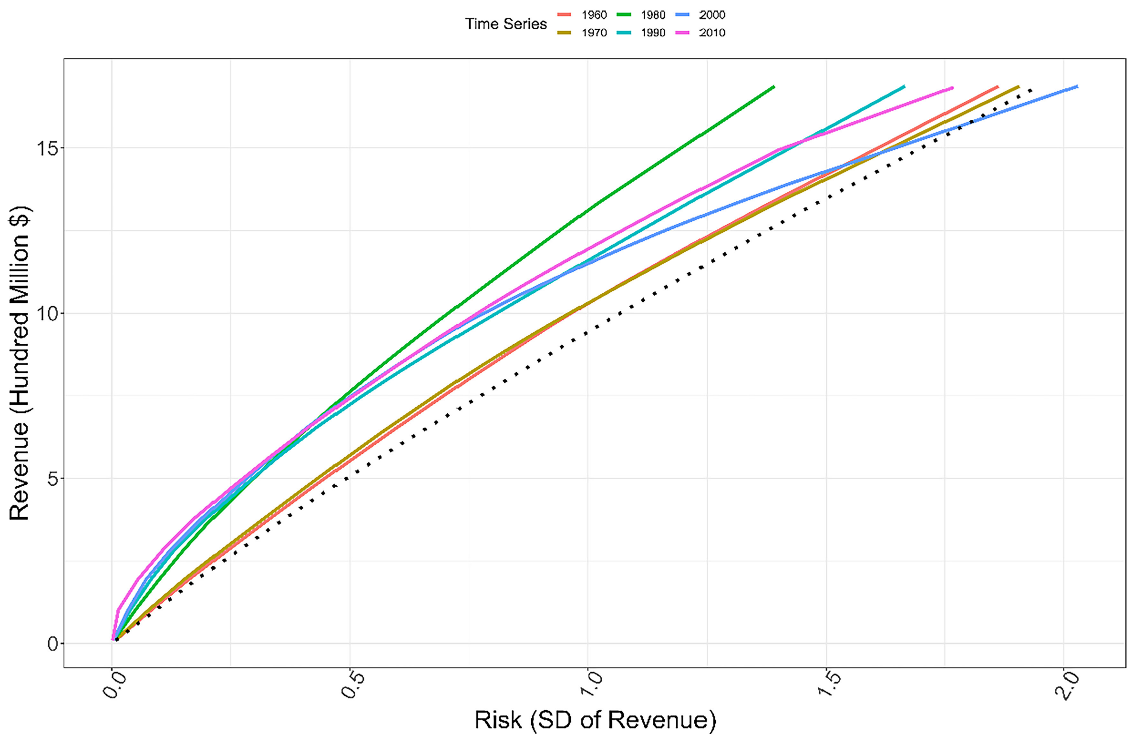


**Figure 9.** Ecosystem-based fisheries management frontiers created for the "top 30 taxa" using different length time series and a decay factor and sustainability parameter = 1. The black dotted line represents the full time series available to download (1950–2021). "1960" (red) represents the frontier created from data between 1960 and 2021 and so on. Thus, "2010" (pink) represents the frontier made from the shortest time series (2010–2021).

However, the underlying revenue weights and frontier position will vary from shifts in portfolio landings magnitude and composition and the current implementation of the biological constraints (using maximum annual harvest for each species from the beginning of the time series until time $t$), as well as differences in the covariance matrices. Once the frontier is constructed, a fishery manager can select where on the frontier to operate, depending on their risk tolerance.

## DISCUSSION

Portfolio theory is a commonly applied, successful financial tool that can be adapted to EBFM for balancing risk with expected benefits for a portfolio of species, so this method warrants further consideration as we try to transition away from single-species fisheries management to more holistic ecosystem approaches. We combined and applied the methods developed by Sanchirico et al. (2008) and Jin et al. (2016) to demonstrate how the portfolio approach can be applied to publicly available fishery data. We made code publicly available with guidance on protocols to promote further use of portfolio theory in fisheries, provide best practice recommendations, and provide resources (i.e., code) so that these case studies can be conducted by noneconomists.

Like all methods, portfolio theory has embedded assumptions. When fitting the portfolio, it is assumed that the distribution of revenue (e.g., its expected value and relevant unconditional higher moments of the distribution) are stationary and can be accurately estimated. The method is vulnerable to systematic risk, such as infrequent shock, which affects most assets in a portfolio (Engle, 2011). In the financial world, this occurred during the dot-com crash of the early 2000s, the 2008 financial crisis, and the COVID-19 pandemic. In fisheries, system risk can occur when fisheries collapse (e.g., the New England groundfish fishery; Healey, 2000), when natural disasters occur, or when there are potential ecological regime shifts. Additionally, this method is reliant on historical data and assumes that the portfolio fit to historical data is representative of current conditions. Unfortunately, past performance in fisheries is not always indicative of current or future performance. Misspecification of the optimized value function, by, for example, selecting a mean-variance representation and ignoring important higher moments of the distribution, can compound these issues (Engle, 2011). In addition, stock dynamics play an integral role in species availability and the performance of the portfolio by defining the biological constraints of the system. The simplistic treatments of these constraints in the exploratory analysis presented here should be revisited prior to any management application. Thus, analysts need to strongly consider the composition and temporal scale of the portfolio, the distribution of the returns themselves, and the most appropriate conservation constraints when designing a portfolio analysis.

An assumption made with our demonstration and in other fishery portfolio approaches is that revenue reflects value. However, the value of a fishery can be considered using a range of metrics (e.g., through profits or net economic value) with varying quality. At one extreme (e.g., recreational or subsistence fisheries), the only available information is landings (number or weight of landed fish, without extensive evaluations of socioeconomic value). At the other extreme, revenue, costs, or even social value are available. We demonstrate that portfolio analyses can be informative with the best scientific information available. As a metric of value, revenue is of intermediate quality with which to evaluate benefits of coordinated management, given that it lacks consideration of any differential costs of fishing across species. However, the implicit assumption of equal costs between single-species and more coordinated multispecies management needs to be considered in the definition of a portfolio and interpretations. For example, targeting species that are caught in the same fishing trip may incur negligible marginal costs between single-species and multispecies management scenarios. By contrast, gear switching or moving home port may be required to differentially target other species in a regional portfolio, and those costs should be considered in interpretations if substantial fleet homogeneity exists. Alternatively, portfolios can be defined as species groups that would incur similar costs between single-species and multispecies management scenarios.

The results presented here corroborate findings from previous fisheries portfolio studies (Carmona et al., 2020; Jin et al., 2016; Sanchirico et al., 2008), demonstrating that historical economic performance is suboptimal when compared to the single species and EBFM frontiers; needless risk was taken to achieve the observed revenue. In this demonstration, the mix of species historically harvested consistently bore unnecessary risk (i.e., the frontier did not extend over and above point b [Figure 1]) despite optimized portfolios operating within the biological system constraints.

While we focused on commercial landings from New England, the NMFS Landings database collates commercial (and recreational) landings data for seven other regions: Alaska, Gulf, Hawaii, Middle Atlantic, Pacific Coast, South Atlantic, and the Great Lakes, as well as five U.S. territories: Guam, American Samoa, Northern Mariana Islands, U.S. Virgin Islands, and Puerto Rico. Although there is significant variation in the length of the historical time series between regions (e.g., Hawaii has data from 2011 onwards), this provides opportunity for analyses to assess how U.S. commercial fisheries are performing on a regional and national level (Townsend et al., 2024) compared to how they could perform if operating on an EBFM frontier. Further, this demonstration arbitrarily used the top 30 taxa by landings weight, but this may not be a practical portfolio composition to implement from a management perspective. Instead, analyses could focus on species managed by the respective fishery management councils to produce regional portfolios. Analysts should collaborate with regional councils and other stakeholders to determine which species, scales, and time periods would be most beneficial for portfolio analyses. We worked with the New England Fisheries Management Council Scientific and Statistical Committee (e.g., Brewster et al., 2023a). This group provided valuable feedback (e.g., conducting sensitivity analysis, displaying the species composition for various target revenues on the frontier to make it more intuitive for stakeholders) as well as recommendations that would make it more beneficial and actionable for management. Developing a risk aversion profile for the council to determine where they would operate on the EBFM frontier would allow the analyst to focus on the frontier range most useful for managers. Further, we recommend seeking industry input. For example, fishermen may be able to explain how market conditions have driven decisions that impact landings (and therefore the observed revenue) and whether the optimal landings in a portfolio are realistic for them.

Portfolio theory could be valuable for bilateral and international management of fisheries. For example, the United States and Canada co-manage historically important groundfish species on Georges Bank. Conducting portfolio analysis on these species, using a combination of landings time series (combined; United States only and Canada only) would allow fishery managers to have a better understanding of trade-offs between revenue and risk for each country. Similarly, this could be useful for U.S. domestic stocks that are shared across fishery management councils and other international organizations (e.g., International Commission for the Conservation of Atlantic Tunas and International Council for the Exploration of the Sea), where quotas are routinely split between different nations. Conducting sensitivity analyses from different scenarios would allow fishery managers in each region to determine which levels of risk and revenue they are comfortable with.

Climate change is well recognized as a driver of marine population dynamics and fisheries interactions (Barange et al., 2018). The region used in this study, the Northwest Atlantic, has warmed faster than many other regions globally (Pershing et al., 2021). Many species that support important commercial or recreational fisheries in this region have exhibited changes in distribution or productivity in response to climate change (Saba et al., 2023). Certain species are predicted to be more productive under future climate conditions (i.e., climate change "winners"; e.g., Black Sea Bass *Centropristis striata* and Butterfish *Peprilus triacanthus*), while others may be negatively impacted (i.e., climate change "losers"; e.g., Atlantic Cod, Yellowtail Flounder; Hare et al., 2016). Thus, it is important that analysts consider climate change impacts on species trends and relationships when composing the portfolio to ensure that negative covariances are emphasized in the covariance matrix. For the portfolio approach to be successful (i.e., achieve low variance and outperform the single-species frontier), the portfolio composition must be adaptive to exploit negative covariances. For example, cross-jurisdictional governance may be needed to allow access to species that have expanding spatial distributions (e.g., Mid-Atlantic Fisheries Management Council , 2022).

The fishery analyst or managers will need to consider the sustainability parameter ($\gamma$). In the demonstrated example, we set $\gamma = 1$, which assumes that the maximum historical landings are sustainable removals. However, this has not always been the case, especially in areas with a long fishing history, such as New England. Further, landings are not total removals, and for some species, discards or recreational catch might be a higher proportion of removals. Aggregating landings also does not account for differences between stocks (e.g., size and growth). One option is to add a decay factor to the maximum historical landings to ensure that the biological constraint is more consistent with current fishing conditions. Alternatively, an analyst could consider using maximum sustainable yield (MSY)—which is the long-term sustainable harvest and is used in management for most species—to inform the sustainability parameter. However, MSY or MSY proxies are typically calculated as part of single-species stock assessments and thus are not always available for every species. Where single-species reference points are available, they may be summed, but this ignores broader ecological interactions and can result in higher estimates than those estimated by aggregate models (Fogarty et al., 2012; Lucey et al., 2012). More work is needed in the future to improve application of the sustainability constraint.

Portfolio theory is not able to estimate resource or fishery status. However, fisheries management councils should consider using this method as a complement to single-species stock assessments. Portfolio theory can provide holistic estimates of revenue and risk for an entire ecosystem but is not able to estimate changes in biology and fine-scale fishery interactions. Stock assessments are designed to estimate fishery interactions and population dynamics but do not explicitly account for the trade-off between species and differences in associated revenue. Portfolio theory could also be used to identify species that are of economic importance and are economically depressed. Additionally, routinely evaluating the risk gap for a portfolio in a given management jurisdiction will provide a clearer sense of fisheries performance and should become a key part of reporting on stocks in a fishery. Thus, we recommend that fishery managers use portfolio theory in collaboration with single-species stock assessments to provide a better understanding of trade-offs in the ecosystem while still being able to use stock assessments to understand fine-scale fishery interactions and estimate reference points.

A limitation to using publicly available data is confidential landings. When a species is landed by only a few vessels (typically $\leq 3$), the landings and revenue data are aggregated with other such species to prevent public access to business information. The impact of this on the portfolio can vary depending on both the number of species in the portfolio that contribute to confidential landings and the quantity of landings masked under that designation. When considering a portfolio composition for management, an analyst would ideally have full access to landings and revenue data.

Future research should focus on developing a projection methodology so that risk and revenue values can be estimated in the future. A significant amount of work has been done in the financial field for projecting investment portfolios into the future (Yu et al., 2020). It is possible that these methods could be adapted for fisheries portfolios. Projections would allow fishery managers to consider future trade-offs when determining fishing quotas. Additionally, evaluation of projection performance would be another diagnostic that analysts could use to improve their portfolios. Future work should also look to extend the portfolio approach to include recreational catch, which would be particularly important in areas such as the southeast United States, where saltwater anglers can contribute significantly to population removals of some species (Shertzer et al., 2019).

Portfolio analysis considers interactions among assets that comprise an investment portfolio to reduce the risk of achieving target levels of economic returns. This approach has been used successfully in finance, and several studies have demonstrated its potential utility in fisheries, particularly in light of the push towards integrated ecosystem considerations. A portfolio approach to fisheries management can offer multiple benefits to managers, such as the ability to use readily available data, to provide valuable insight into species interactions, and to quantify risk–revenue trade-offs (e.g., lower risk of not achieving target revenue) that can be gained from multispecies management (e.g., coordinated management of multispecies portfolio that takes advantage of asynchronous patterns of productivity among taxa). Another potential benefit of portfolio theory is its ability to distinguish priority species for stock rebuilding. The covariance matrix and sensitivity analysis indicate which species most influence portfolio performance (i.e., those contributing the strongest negative covariance) and would be most beneficial for councils to focus recovery efforts on. Additionally, optimal taxa weights can help to identify specific catch limits that may constrain targeted fishing for other species (e.g., choke stocks). By making use of historic data, current data collection practices would not have to be revised for this approach to be implemented as a tool for use by managers. While this demonstration utilized publicly available data, more comprehensive data accounting for confidential landings could also be used. Nonetheless, application of this tool has been limited, and one potential barrier is lack of digestible implementation guidelines for the noneconomist. Thus, this paper provides a framework to assist the noneconomist in applying portfolio theory in a fisheries context in the hope that fishery managers will more readily consider this method as part of their ecosystem-based fisheries management toolbox.

## SUPPLEMENTARY MATERIAL

Supplementary material is available at *North American Journal of Fisheries Management* online.

## DATA AVAILABILITY

Data available at www.fisheries.noaa.gov/foss, and the data file and R script used for this demonstration are available at github.com/lauranbrewster/multispecies_portfolios.

## ETHICS STATEMENT

There were no ethical guidelines applicable to this study.

## FUNDING

This project is funded by the Lenfest Ocean Program (Pew Charitable Trusts Grant Agreement 00035254); the Walton Family Foundation (Grant 00109688); and National Oceanic and Atmospheric Administration, Cooperative Institute for the North Atlantic Region (NA19OAR4320074).

## CONFLICTS OF INTEREST

The authors declare no conflict of interest.

## ACKNOWLEDGMENTS

We appreciate guidance from our steering committee (Jeffrey Buckel, Chip Collier, Scott Crosson, Christopher Dumas, Rob

Griffin, Lisa Kerr, Douglas Lipton, Michael Ruccio, and John Walden) as well as input to the demonstration portfolio from the New England Fishery Management Council's Scientific and Statistical Committee.

## REFERENCES


Baker, H. K., & Filbeck, G. (Eds.). (2013). *Portfolio theory and management*. Oxford University Press.

Barange, M., Tarûb, B., Beveridge, M. C. M., Cochrane, K. L., Funge-Smith, S., & Poulain, F. (2018). *Impacts of climate change on fisheries and aquaculture: synthesis of current knowledge, adaptation and mitigation options* (Fisheries and Aquaculture Technical Paper 627). Food and Agriculture Organization of the United Nations.

Brewster, L. R., Edwards, F., Link, J., & Cadrin, S. X. (2023a). *Using portfolio theory to improve the management of living marine resources: A demonstration for New England fisheries*. New England Fishery Management Council, Scientific and Statistical Committee. https://d23h0vhsm26o6d.cloudfront.net/2a_Portfolio-Analyses-of-New-England-Fisheries_2023-07-11-172012_sjvm.pdf

Brewster, L. R., Edwards, F., Link, J., & Cadrin, S. X. (2023b). *Using portfolio theory to improve the management of living marine resources: A demonstration for South Atlantic fisheries*. South Atlantic Fishery Management Council, Scientific and Statistical Committee and Socioeconomic Panel. https://safmc.net/documents/sep_a5a_portfolio-analyses-of-south-atlantic-fisheries-pdf/

Brodziak, J., & Link, J. (2002). Ecosystem-based fishery management: What is it and how can we do it? *Bulletin of Marine Science*, *70*, 589–612.

Carmona, I., Ansuategi, A., Chamorro, J. M., Escapa, M., Gallastegui, M. C., Murillas, A., & Prellezo, R. (2020). Measuring the value of ecosystem-based fishery management using financial portfolio theory. *Ecological Economics*, *169*, Article 106431. https://doi.org/10.1016/j.ecolecon.2019.106431

Condylios, S. (2022). priceR: Economics and pricing tools. R package version 1.0.2. https://cran.r-project.org/package=priceR

Curtis, G. (2004). Modern portfolio theory and behavioral finance. *The Journal of Wealth Management*, *7*, 16–22. https://doi.org/10.3905/jwm.2004.434562

DuFour, M. R., May, C. J., Roseman, E. F., Ludsin, S. A., Vandergoot, C. S., Pritt, J. J., Fraker, M. E., Davis, J. J., Tyson, J. T., & Miner, J. G. (2015). Portfolio theory as a management tool to guide conservation and restoration of multi-stock fish populations. *Ecosphere*, *6*, Article 296. https://doi.org/10.1890/ES15-00237.1

Edwards, S. F., Link, J. S., & Rountree, B. P. (2004). Portfolio management of wild fish stocks. *Ecological Economics*, *49*, 317–329. https://doi.org/10.1016/j.ecolecon.2004.04.002

Edwards, S. F., Link, J. S., & Rountree, B. P. (2005). Portfolio management of fish communities in large marine ecosystems. *Large Marine Ecosystems*, *13*, 181–199. https://doi.org/10.1016/S1570-0461(05)80032-1

Engle, R. F. (2011). Long-term skewness and systemic risk. *Journal of Financial Econometrics*, *9*, 437–468. https://doi.org/10.1093/jjfinec/nbr002

Fogarty, M. J., Overholtz, W. J., & Link, J. S. (2012). Aggregate surplus production models for demersal fishery resources of the gulf of Maine. *Marine Ecology Progress Series*, *459*, 247–258. https://doi.org/10.3354/meps09789

Halpern, B. S., White, C., Lester, S. E., Costello, C., & Gaines, S. D. (2011). Using portfolio theory to assess tradeoffs between return from natural capital and social equity across space. *Biological Conservation*, *144*, 1499–1507. https://doi.org/10.1016/j.biocon.2011.01.019

Hare, J. A., Morrison, W. E., Nelson, M. W., Stachura, M. M., Teeters, E. J., Griffis, R. B., Alexander, M. A., Scott, J. D., Alade, L., & Bell, R. J. (2016). A vulnerability assessment of fish and invertebrates to climate change on the northeast U.S. Continental shelf. *PLoS One*, *11*, Article e0146756. https://doi.org/10.1371/journal.pone.0146756.

Healey, T. H. M. (2000). Ludwig's ratchet and the collapse of new England groundfish stocks. *Coastal Management*, *28*, 187–213. https://doi.org/10.1080/089207500408629

Hilborn, R., & Walters, C. J. (1992). *Quantitative fisheries stock assessment: Choice, dynamics and uncertainty*. Chapman & Hall.

J. P. Morgan/Reuters. (1996). RiskMetrics: Technical document (4th ed.). https://www.msci.com/documents/10199/5915b101-4206-4ba0-aee2-3449d5c7e95a

Jin, D., DePiper, G., & Hoagland, P. (2016). Applying portfolio management to implement ecosystem-based fishery management (EBFM). *North American Journal of Fisheries Management*, *36*, 652–669. https://doi.org/10.1080/02755947.2016.1146180

Karatzoglou, A., Smola, A., & Hornik, K. (2024). kernlab: Kernel-based machine learning lab. R package version 0.9-33. https://CRAN.R-project.org/package=kernlab

Karp, M. A., Link, J. S., Grezlik, M., Cadrin, S., Fay, G., Lynch, P., Townsend, H., Methot, R. D., Adams, G. D., Blackhart, K., Barceló, C., Buchheister, A., Cieri, M., Chagaris, D., Christensen, V., Craig, J. K., Cummings, J., Damiano, M. D., Dickey-Collas, M., … Trijoulet, V. (2023). Increasing the uptake of multispecies models in fisheries management. *ICES Journal of Marine Science*, *80*, 243–257. https://doi.org/10.1093/icesjms/fsad001

Link, J. S., Gamble, R. J., & Fogarty, M. J. (2011). *An overview of the NEFSC's ecosystem modeling enterprise for the northeast US shelf large marine ecosystem: Towards ecosystem-based fisheries management* (Northeast Fisheries Science Center Research Document 11-23). National Marine Fisheries Service.

Lucey, S. M., Cook, A. M., Boldt, J. L., Link, J. S., Essington, T. E., & Miller, T. J. (2012). Comparative analyses of surplus production dynamics of functional feeding groups across 12 northern hemisphere marine ecosystems. *Marine Ecology Progress Series*, *459*, 219–229. https://doi.org/10.3354/meps09825

Lynch, P. D., Methot, R. D., & Link, J. S. (Ed.). (2018). *Implementing a next generation stock assessment enterprise* (Technical Memorandum NMFS-F/SPO-183). National Oceanic and Atmospheric Administration.

Meyer, J. (1987). Two-moment decision models and expected utility maximization. *The American Economic Review*, *77*, 421–430.

Mid-Atlantic Fisheries Management Council. (2022). *East Coast climate change scenario planning: Final scenario narratives, November 2022*. https://static1.squarespace.com/static/511cdc7fe4b00307a2628ac6/t/636563a0daf96c30ba5cf9f8/1667589025882/ECSP+Scenario+Narratives_Nov+2022.pdf.

National Marine Fisheries Service. (2016). *NOAA Fisheries ecosystem-based fisheries management road map* (Procedure 01-120-01). https://www.fisheries.noaa.gov/s3//dam-migration/01-120-01.pdf

Perruso, L., Weldon, R. N., & Larkin, S. L. (2005). Predicting optimal targeting strategies in multispecies fisheries: A portfolio approach. *Marine Resourced Economics*, *20*, 25–45. https://doi.org/10.1086/mre.20.1.42629457

Pershing, A. J., Alexander, M. A., Brady, D. C., Brickman, D., Curchitser, E. N., Diamond, A. W., McClenachan, L., Mills, K. E., Nichols, O. C., & Pendleton, D. E. (2021). Climate impacts on the gulf of Maine ecosystem: A review of observed and expected changes in 2050 from rising temperatures. *Elementa*, *9*, Article 00076. https://doi.org/10.1525/elementa.2020.00076

Radulescu, M., Rădulescu, C. Z., Rahoveanu, M. T., & Zbăganu, G. (2010). A portfolio theory approach to fishery management. *Studies in Informatics and Control*, *19*, 285–294. https://doi.org/10.24846/v19i3y201008

R Core Team. (2022). R: A language and environment for statistical computing. R Foundation for Statistical Computing. https://www.R-project.org/

Rosenberg, A. A., Swasey, J. H., & Bowman, M. (2006). Rebuilding US fisheries: Progress and problems. *Frontiers in Ecology and the Environment*, *4*, 303–308. https://doi.org/10.1890/1540-9295(2006)4[303:RUFPAP]2.0.CO;2

Saba, V., Borggaard, D., Caracappa, J. C., Chambers, R. C., Clay, P. M., Colburnid, L. L., Deroba, J., DePiper, G., Du Pontavice, H.,

& Fratantoni, P. (2023). NOAA fisheries research geared towards climate-ready living marine resource management in the northeast United States. *PLoS Climate*, *2*, Article e0000323. https://doi.org/10.1371/journal.pclm.0000323

Sanchirico, J. N., Smith, M. D., & Lipton, D. W. (2008). An empirical approach to ecosystem-based fishery management. *Ecological Economics*, *64*, 586–596. https://doi.org/10.1016/j.ecolecon.2007.04.006

Schindler, D. E., Hilborn, R., Chasco, B., Boatright, C. P., Quinn, T. P., Rogers, L. A., & Webster, M. S. (2010). Population diversity and the portfolio effect in an exploited species. *Nature*, *465*, 609–612. https://doi.org/10.1038/nature09060

Shepherd, G., Cieri, M., Power, M., & Overholtz, W. (2009). *Transboundary resources assessment committee Gulf of Maine/Georges Bank Atlantic herring stock assessment update (*Reference Document 2009/04*)*. Fisheries and Oceans Canada and National Marine Fisheries Service.

Shertzer, K. W., Williams, E. H., Craig, J. K., Fitzpatrick, E. E., Klibansky, N., & Siegfried, K. I. (2019). Recreational sector is the dominant source of fishing mortality for oceanic fishes in the southeast United States Atlantic Ocean. *Fisheries Management and Ecology*, *26*, 621–629. https://doi.org/10.1111/fme.12371

Smith, A. D. M., Fulton, E. J., Hobday, A. J., Smith, D. C., & Shoulder, P. (2007). Scientific tools to support the practical implementation of ecosystem-based fisheries management. *ICES Journal of Marine Scienc*, *64*, 633–639. https://doi.org/10.1093/icesjms/fsm041

Townsend, H., Link, J., Piper, G. D., Brewster, L. R., Cadrin, S. X., & Edwards, F. (2024). Multispecies portfolios of U.S. marine fisheries: Ecosystem-based fisheries management reduces economic risk. *Fisheries*, *49*, 536–547. https://doi.org/10.1002/fsh.11152

Vanderbei, R. J. (1999). LOQO: An interior point code for quadratic programming. *Optimization Methods & Software*, *11*, 451–484. https://doi.org/10.1080/10556789908805759

Wei, T., & Simko, V. (2024). corrplot: Visualization of a correlation matrix. R package Version 0.95. https://cran.r-project.org/package=corrplot.

Yang, M. M., Sharp, B. M. H., & Sbai, E. (2008). *A portfolio approach for the New Zealand multi-species fisheries management* [Paper presentation]. New Zealand Agricultural and Resource Economics Society 2008 Conference, Nelson, New Zealand.

Yu, J. R., Paul Chiou, W. J., Lee, W. Y., & Lin, S. J. (2020). Portfolio models with return forecasting and transaction costs. *International Review of Economics & Finance*, *66*, 118–130. https://doi.org/10.1016/j.iref.2019.11.002