Towards ecosystem-based fisheries management in an economically constrained context: Giving more consideration to the ecosystem approach to fisheries management

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SEDAR103-RD-27

Fisheries Research 301 (2026) 107841

Contents lists available at ScienceDirect

Fisheries Research

journal homepage: www.elsevier.com/locate/fishres

Review

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A R T I C L E I N F O

Handled by Andre Eric Punt

Keywords:
Ecosystem approach to fisheries management
Ecosystems
Fisheries management
Mixed fishery
Multivariate statistics

A B S T R A C T

Achieving ecosystem-based fisheries management (EBFM), which seeks to optimise fisheries catches whilst maintaining the structure and functioning of ecosystems, is becoming more challenging in the current context associated with budget cuts and the restructuring of many research and management institutions. As such, more consideration could be given to the ecosystem approach to fisheries management (EAFM) which focuses on individual fisheries, to build strong foundations for EBFM. Here, we report an approach we developed to identify relevant tools to assist EAFM in New Zealand, towards EBFM. We present it and demonstrate it through an application to the west coast South Island (WCSI). Our application includes principal component analyses (PCAs) and heatmaps on landing compositions from the WCSI mixed bottom trawl fishery and research survey biomasses. Analyses indicated that the last 34 years can be divided into four clusters, starting with a period where the biomasses and landings of flatfishes and associated bycatch species were particularly high and ending with a period where the biomasses and landings of the commercially valuable snapper (*Chrysophrys auratus*) and red gurnard (*Chelidonichthys kumu*) increased markedly. Using the literature and knowledge from resource managers and stakeholders, we were able to interpret the clusters of years in light of changes from natural or anthropogenic causes. For example, the increased snapper biomass and landings in the most recent years may be partly explained by warming and more regular marine heatwaves that benefited the snapper population. The tools we identified will help progress EAFM in New Zealand and can support current management in several ways. In particular, user-friendly visual analyses based on PCAs and heatmaps and métier analysis can contribute to a better framework for defining fisheries, by delivering an understanding of catch composition as an emergent

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https://doi.org/10.1016/j.fishres.2026.107841
Received 8 June 2026; Received in revised form 6 August 2026; Accepted 7 August 2026
Available online 11 August 2026

property of fisheries. We recommend further applications of the tools we identified in New Zealand, and our approach can also be adapted in other world regions.

1. Introduction

Ecosystem-based fisheries management (EBFM) seeks to optimise fisheries catches whilst maintaining the structure and functioning of ecosystems. EBFM has been progressed worldwide over recent decades, although concepts behind EBFM and "ecosystem thinking" have existed in indigenous cultures for centuries (Department of Conservation, 2020; Link and Marshak, 2021). EBFM recognises the biological, physical, economic and social complexities of ecosystems to manage multiple fisheries (NOAA, 2018). Ecosystem-based management (EBM) extends the focus of EBFM, to take into account not only fisheries but also all other marine uses, as well as all components of the ecosystem of interest, including humans (Levin et al., 2014). More restricted in scope, the ecosystem approach to fisheries management (EAFM) consists of incrementally adding ecosystem considerations into the existing management of a specific fishery, thereby accounting for variability in some of the ecosystem underlying that fishery (NOAA, 2018).

EBFM has been considered and progressed in different ways across the world. Some countries and regions have afforded extensive EBFM programmes and integrated ecosystem assessments (IEAs) (e.g., the USA; NOAA, 2018; European Union countries; Clay et al., 2023; South Africa; Bornman et al., 2025). However, progress to operationalise EBFM has been slow, and EBFM operationalisation has often been unsuccessful due to the layers of complexity involved (Levin et al., 2014; Skern-Mauritzen et al., 2016; Cormier et al., 2017). There is a depth and breadth of knowledge required to develop EBFM, due to the extensive consultation process with resource managers and stakeholders needed to fully take into account the economic and social impacts and benefits that fisheries have (Harvey et al., 2025). More recently, the economically constrained context globally and resulting budget cuts and restructuring of many research and management institutions have further slowed down progress and have even led to the removal of some EBFM programmes or initiatives worldwide. As such, EBFM in most countries and regions is facing challenging circumstances where available resources are increasingly limiting the ability to meet the goals and ambitions of EBFM, EBM and IEAs (e.g., the Changing Ecosystem and Fisheries Initiative (CEFI) was compromised in the USA; Roskar et al., 2025).

Contrary to a common misconception, most countries and regions implement EBFM to some degree, although often indirectly (Cryer et al., 2016; Karnauskas et al., 2021). For example, in New Zealand, the current management framework incorporates ecosystem considerations into fisheries management advice (Cryer et al., 2016; Appendix A1). Specifically, ecosystem considerations for fisheries management are specified in multiple sections of the Fisheries Act 1996, calling for attention to technical interactions (several species being caught together in the same fisheries operations), trophic interactions, environmental effects on fishes and fisheries, and cumulative impacts of fishing together with other impacts. Fisheries New Zealand, the government department responsible for fisheries management in New Zealand, reports ecosystem considerations in several documents (the New Zealand Fisheries Assessment Plenary and the Aquatic Environment and Biodiversity Annual Review), which are incorporated into consultation documents and decision advice for sustainability rounds and other regulatory changes, to ultimately support decision-making. There have also been efforts in New Zealand to develop more collaborative processes towards combining environmental and stakeholder values, improve environmental performance through the identification of habitats of significance, develop threat management plans and risk assessment frameworks, and encourage innovations to avoid, remedy, or mitigate the environmental impacts of fishing (e.g., impacts to the benthos, protected species bycatch or other finfish bycatch).

Notably, New Zealand funded NZ$71.1 million of EBFM research through the Sustainable Seas National Science Challenge programme over 10 years (2014–2024). The Sustainable Seas National Science Challenge allowed for several EBFM and EBM projects in New Zealand, albeit mostly programmatic or pilot studies (e.g., McGregor et al., 2021; Allison, 2022; Ellis et al., 2025; Flowers et al., 2025). Besides the Sustainable Seas National Science Challenge programme, resources for EBFM research in New Zealand have always been modest, but they have become even more limited since the end of the programme in June 2024 (Mace et al., 2014; Durante et al., 2020).

Given the current challenges faced by EBFM research, more consideration could be given to EAFM, to build simpler yet strong foundations for EBFM. EAFM is the necessary intermediate step between single-species fisheries management and EBFM, to ultimately reach EBM (NOAA, 2018). In New Zealand, it is realistic to progress EAFM before EBFM projects such as the research initiated within the Sustainable Seas National Science Challenge are continued.

Here, we report on an approach developed in New Zealand to assist in the transition towards EBFM. Our approach aims to build strong EAFM foundations that will, in the future, be conducive to operational EFBM, and it can be adapted in other world regions. In the present paper, we pursue two objectives: (i) utilising our approach to assess EBFM tools from an EAFM perspective for New Zealand; and (ii) carrying out a first application of tools identified by our approach to the inshore mixed bottom trawl fishery operating off the west coast South Island and within fisheries management area 7 (FMA 7) (Fig. 1). This

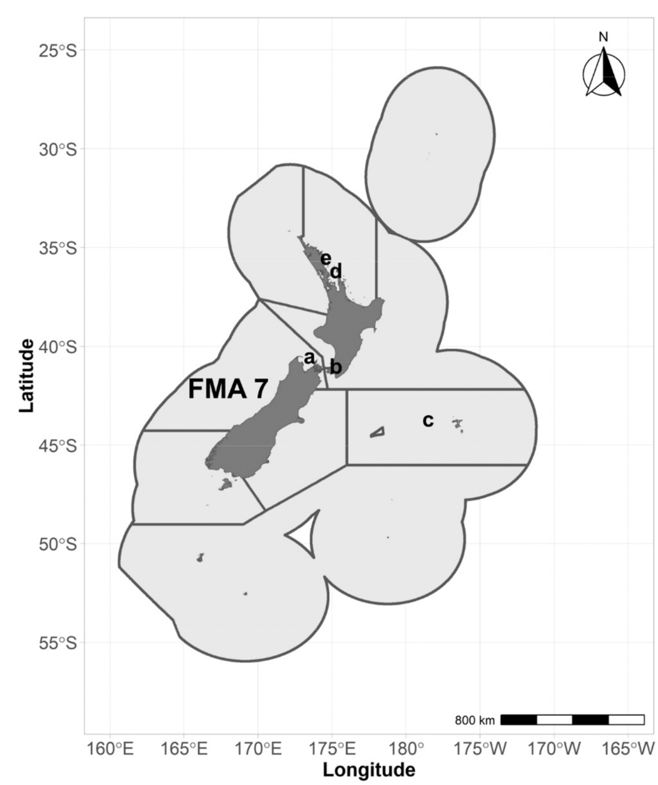

Fig. 1. Map of New Zealand's exclusive economic zone showing the ten New Zealand fisheries management areas (FMAs; polygons filled in light grey). The location of FMA 7, which is the focus of the present study, is indicated. Important features are labelled and include: (a) Tasman Bay/Golden Bay; (b) Wellington south coast; (c) the Chatham Rise; (d) the Hauraki Gulf; and (e) the Whangārei region.

first application (which can be followed by other applications with future funding) relied on principal component analyses (PCAs) and heatmaps, which allowed for an "ecosystem characterisation." This ecosystem characterisation provided insights into changes in the ecological footprint of the mixed bottom trawl fishery in FMA 7 and stock interactions over time, which we could also relate to qualitative knowledge, environmental information, and management interventions in the ecosystem. Compared to more sophisticated multivariate approaches, PCAs and heatmaps are relatively straightforward to undertake and are easily communicated. This translates into methods that have been exceptionally valuable for providing a clear big picture of dynamics in FMA 7 and, therefore, solid bases for EAFM in the region. We argue that the efforts reported in the present study, and related efforts, can advance region-specific EAFM in New Zealand and elsewhere, specifically in regions where resources may be limited, with an ultimate goal of achieving EBFM.

2. Methods

Our approach focuses on assessing EBFM tools from an EAFM perspective. As such, our approach starts with a review of (i) relevant EBFM tools for the marine region of interest given fisheries managers' priorities and interests and (ii) EBFM efforts to date in that marine region. Next, based on the review of EBFM tools and consultations with resource managers, stakeholders and experts, our approach identifies and ranks the EBFM tools that are relevant to EAFM in the marine region of interest. In the application of our approach to FMA 7, the primary focus was on the issue of technical interactions (several species being caught together in the same fisheries operations), because technical interactions are one of the current priorities of fisheries management in New Zealand. Based on our review of EBFM tools and efforts in New Zealand, consultations with resource managers and stakeholders, and workshops with international experts, we: (i) identified EBFM tools relevant to New Zealand EAFM case studies; (ii) invited expert input on experiences with these tools overseas; and (iii) ranked these tools based on specific requirements (detailed below). As a first application of our approach, we also implemented those tools that ranked the highest and were deemed the first ones viable to employ in support of EAFM in New Zealand, namely PCAs and heatmaps applied to landing composition and research survey biomass data for FMA 7.

2.1. EBFM tools

New Zealand has experienced decades of EBFM research but there was no inventory of the tools relevant for EBFM in New Zealand. We produced this inventory, with a primary focus on the tools that can be operationalised under New Zealand's current management framework. To generate this inventory, we relied on: (i) a literature review; (ii) consultations with fisheries managers, fishing industry representatives, and other stakeholders; and (iii) workshops with international experts (Appendix A2). While producing this inventory, we took stock of the applications of the inventoried EBFM tools in New Zealand to date.

2.2. EBFM tools most relevant for EAFM in New Zealand

We built on our inventory of EBFM tools (Section 2.1) to identify EAFM tools for New Zealand, with a primary focus on the issue of technical interactions (one of the current priorities of fisheries management in New Zealand). We qualitatively ranked the identified EAFM tools, based on: (i) the questions they can answer/their outputs, considering the importance of answerable questions to fisheries management in New Zealand; (ii) the requirements of the tools; (iii) their advantages and limitations; and (iv) the resources available in New Zealand to apply them (funding and expertise). Each EAFM tool was assigned a low, medium, high, or very high rank.

2.3. FMA 7 case study

In the present study, we also demonstrated our approach through a first application to the inshore mixed bottom trawl fishery operating in FMA 7. FMA 7 can be subdivided into three main subregions: the west coast; Tasman Bay/Golden Bay; and the northeast coast (Fig. 1 and Appendix A3). FMA 7 is characterised by strong seasonal variation with a number of species migrating between Tasman Bay/Golden Bay (TBGB), the west coast, and various areas and depths (Fisheries New Zealand, 2019). Technical interactions in the FMA 7 inshore mixed bottom trawl fishery are numerous and complex, and catch mixes in the region are dynamic. The SNA 7 snapper (*Chrysophrys auratus*) stock is a particularly economically important stock in the fishery and its population size has increased rapidly from low levels over the last decade (Langley, 2024). Given established snapper catch limits, fishers have modified trawl net headline height, fishing behaviour and areas fished to avoid catching too many snapper, resulting in changed catch mixes in FMA 7 (Fisheries New Zealand, 2019). Other notable stocks in FMA 7 are the GUR 7 red gurnard (*Chelidonichthys kumu*) and TAR 7 tarakihi (*Nemadactylus macropterus*) stocks, which, along with SNA 7, are the only stocks in the inshore mixed bottom trawl fishery with a fully quantitative (age-structured) assessment.

For the FMA 7 case study, we considered a stock complex which included: (i) SNA 7, GUR 7, TAR 7 and the other 12 stocks listed in the National Inshore Finfish Fisheries Plan for the FMA 7 mixed bottom trawl fishery (Fisheries New Zealand, 2022); and (ii) the BAR 7 barracouta (*Thyrsites atun*) and the RSK 7 rough skate (*Zearaja nasuta*) stocks, which were added at the request of fisheries managers and the stakeholders consulted for our research (Table 1).

2.4. Application of PCAs and heatmaps to the FMA 7 case study

Among the tools we identified to support EAFM in New Zealand (Section 3.2), two forms of multivariate analyses, PCAs and heatmaps (a.k.a. "traffic light plots") (Karnauskas et al., 2015) had a very high rank. The primary goal of PCAs and heatmaps is to understand the ecosystem underlying a particular mixed fishery through the composition of the catches. PCA is performed on catch composition, leading to different species groupings through time and the possibility to rapidly identify major species shifts in the ecosystem. Then, a heatmap can be created, which considers how the contribution of species to the catch peaks and changes over time. The heatmap can be annotated to relate the changes in species contributions to major gear shifts, management shifts and/or environmental shifts.

We conducted PCAs and generated a heatmap employing landing composition data for the commercial mixed bottom trawl fishery operating within FMA 7 for fishing years 1992–2024, where fishing years (henceforth simply "years") start on 1st October of the preceding calendar year (Appendix A4). PCAs and the heatmap using landing data helped us characterise the FMA 7 ecosystem based on changes in commercial fisheries landing composition over time. Aware that changes in species compositions in landings could be the result of confounding factors associated with fishing such as changes in gear and catch regulations, we produced a second type of PCAs and heatmap employing research biomass survey data for the same time period (1992–2025, although surveys were not carried out in all years of the study period; Appendix A4). This second type of PCAs and heatmap allowed us to better infer whether changes in fisheries landing composition over the past 34 years may stem from ecological or environmental shifts or changes driven by resource management (e.g., reporting requirements), fishing behaviour (e.g., avoidance of certain species in response to legislation) or market preferences.

Our multivariate analyses were all conducted in the R programming environment and started with applying spectral decomposition to landing composition (total annual landings) or survey relative biomasses through time. We differentiated landing composition and survey

Table 1
Stocks in the fisheries management area 7 (FMA 7) inshore mixed bottom trawl stock complex and levels of information for them. Note that the BAR 7 and RSK 7 stocks were not identified in the stock complex reported in the National Inshore Finfish Fisheries Plan (Fisheries New Zealand, 2022) but were included at the request of fisheries managers and stakeholders due to important interactions with the other stocks.

Stock	Species	Family	Assessment type
SNA 7	Snapper (*Chrysophrys auratus*)	Sparidae	Fully quantitative – age structured model
GUR 7	Red gurnard (*Chelidonichthys kumu*)	Triglidae	Fully quantitative – age structured model
TAR 7	Tarakihi (*Nemadactylus macropterus*)	Cheilodactylidae	Fully quantitative – age structured model
JDO 7	John dory (*Zeus faber*)	Zeidae	Partial Quantitative – catch per unit effort (CPUE) and trawl surveys
STA 7	Stargazer (*Kathetostoma giganteum*)	Uranoscopidae	Partial Quantitative – Trawl survey biomass estimates
FLA 7	Eight flatfish species: yellow-belly flounder (*Rhombosolea leporine*) (YBF); sand flounder (*Rhombosolea plebeian*) (SFL); black flounder (*Rhombosolea retiarii*) (BFL); greenback flounder (*Rhombosolea tapirine*) (GFL); lemon sole (*Pelotretis flavilatus*) (LSO); New Zealand sole (*Peltorhamphus novaezeelandiae*) (ESO); brill (*Colistium guntheri*) (BRI); and turbot (*Colistium nudipinnis*) (TUR)	Rhombosoleidae	Partial Quantitative – CPUE for SFL, ESO, BRI and TUR
ELE 7	Elephant fish (*Callorhinchus milii*)	Callorhinchidae	Partial Quantitative – CPUE
BAR 7	Barracouta (*Thyrsites atun*)	Gempylidae	Partial Quantitative – CPUE
SPO 7	Rig (*Mustelus lenticulatus*)	Triakidae	Partial Quantitative – CPUE and trawl surveys
SCH 7	School shark (*Galeorhinus galeus*)	Triakidae	Partial Quantitative – CPUE and trawl surveys
SSK 7	Smooth skate (*Dipturus innominatus*)	Rajidae	Partial Quantitative – Trawl survey biomass estimates
RSK 7	Rough skate (*Zearaja nasuta*)	Rajidae	Partial Quantitative – Trawl survey biomass estimates
RCO 7	Red cod (*Pseudophycis bachus*)	Moridae	No established management targets – Trawl surveys
WAR 7	Blue warehou (*Seriolella brama*)	Centrolophidae	No established management targets – Trawl surveys
SPE 7	Sea perch (*Helicolenus barathri*)	Scorpaenidae	No established management targets – Trawl surveys
GSH 7	Dark ghost shark (*Hydrolagus novaezealandiae*)	Chimaeridae	No established management targets – Trawl surveys
SPD 7	Spiny dogfish (*Squalus acanthias*)	Squalidae	No established management targets – Trawl surveys

relative biomasses by tracing their trajectories in the PCA space (using the first principal components (PCs)). Spectral decomposition was possible in our study because our number of study stocks did not exceed the number of years in the data time series (17 stocks versus 33 years of landing data and 17 years of survey data). We employed scree plots to determine the percent deviance explained by PCs, to ascertain whether the first two or three PCs would offer a sufficiently good representation of the landing composition and survey relative biomass data. More specifically, we examined whether the first two or three PCs explained at least 50% of the variance in the data. We included year as a variable in the spectral decomposition PCAs as this helped the interpretation of the results without qualitatively changing them.

Next, we used singular value decomposition to seek to identify natural clusters of years in landing composition or survey relative biomasses. This allowed us to check if periods of time were grouped in coherent clusters (as opposed to random assortments) in the plane formed by the first PCs, in which case "regimes" could be more clearly inferred in the landing composition or survey relative biomass data. We also performed hierarchical clustering of the scores per stocks against the PCs (a.k.a. "chronological clustering"), to further infer/confirm regimes in the data, employing the Euclidean metric, Ward criterion, and k-means consolidation (Lê et al., 2008). In addition, using PC loadings and biplots, we mapped stocks to the individual PCs to further characterise the variance patterns seen in the landing composition and survey relative biomass data.

Finally, we generated heatmaps by ranking the catches and relative survey biomasses per individual stock through time. The catches and relative biomasses of each stock had low scores when they were low and high scores when they were high. The scoring matrix was plotted as a heatmap, with "cold" colours associated with low scores (low contributions to landings or low biomasses) and "warm" colours associated with high scores (high contributions to landings or high biomasses). In the heatmap plots, species that displayed similar patterns over time were grouped together (facilitated by a simple clustering). For heatmaps, we relied on the absolute contributions per stock through time rather than on proportions in any one year, to prevent the top target stocks having an exceedingly large influence on analyses. Heatmaps were useful to further infer regimes in the landing composition or survey relative biomass data. To help the interpretation of heatmaps, we consulted the literature, fisheries managers and fishing industry representatives to annotate the heatmaps, to indicate important environmental and management events and modifications of fishing behaviour in the study region.

3. Results

3.1. EBFM tools

Our review of EBFM tools primarily focused on the tools that can be operationalised under New Zealand's current management framework, especially to implement EAFM and address the issue of technical interactions. Through our review, we identified six types of EBFM tools: (i) métier analysis; (ii) mixed fisheries forecasts; (iii) ecosystem models; (iv) management strategy evaluation (MSE); (v) dynamic reference points; and (vi) simple EBFM tools. These different types of EBFM tools can be employed in parallel or in combination (Appendix A5).

Métier analysis is a tool particularly suited to mixed fisheries (Parsa et al., 2020a, 2020b). It quantitatively categorises individual fishing events (e.g., trawl tows) or fishing trips to a "métier", i.e., a fishing activity or strategy defined by area and gear, and, therefore, associated with a particular catch composition as a result (Pascoe et al., 2015). Métier analysis is valuable for estimating catchabilities for other EBFM tools such as mixed fisheries forecasts and some dynamic multispecies models (e.g., ISIS-Fish models) (see the next paragraphs). It is also useful for structuring the fisheries aspects of more complex ecosystem models, and it can provide an ecosystem characterisation for an EAFM case study before other tools are used for that case study. Métier analysis also constitutes a useful basis for making management decisions, e.g., applying interventions, such as specific gear or spatial management measures, at a métier rather than whole-of-fishery level. Métier analysis has been implemented only in a preliminary form in New Zealand so far (e.g., Middleton et al., 2024).

Mixed fisheries forecasts are very near-term projections to explore the consequences of management scenarios (e.g., changes in the total allowable commercial catch (TACC) of a given stock) on several stocks within a mixed fishery. The Fcube (Fleet and Fisheries Forecast) method has long been the most common method for mixed fisheries forecasts (Ulrich et al., 2011). The Fcube method utilises catch and effort information to estimate catch potentials for various stocks caught in a mixed fishery employing chosen métiers, and then quantifies risks of over- and under-quota utilisation for the stocks (Ulrich et al., 2011). More recently developed methods for mixed fisheries forecasts include MixME (Mixed-fishery Multi-stock Evaluation; Pace et al., 2025) and FLBEIA (Bio--Economic Impact Assessment using FLR; Garcia et al., 2017). No mixed fisheries forecasts have been performed in New Zealand so far.

Ecosystem models represent central tools for EBFM. They have different characteristics given their differing degree of complexity and their different purposes/objectives. Given the diversity and importance of ecosystem models, we review them in more detail in Section 3.2.

MSE is a framework employing simulations to evaluate trade-offs in performance among candidate management strategies (Punt et al., 2016a). MSE frameworks include an operating model which describes fish and fisheries dynamics, which can be an ecosystem model. In New Zealand, MSEs have already been carried out for several species and stocks and, so far, this use of MSEs has relied on a single-species operating model (Appendix A5).

Dynamic reference points (as opposed to stationary reference points) include primarily dynamic B_0 (dynamic biomass in the absence of fishing), which calculates a theoretical biomass trajectory representing stock size if the stock had never been fished, assuming all other parameters remain as estimated in the stock assessment (Bessell-Browne et al., 2024). Traditionally, stock assessments utilise the B_0 estimate from the first assessment year and consider this to be the “unfished” level of biomass, while dynamic B_0 takes into account temporal variation due to causes other than fishing (e.g., environmental changes) (Bessell-Browne et al., 2024). A few New Zealand projects have explored dynamic reference points. For example, Marsh et al. (2024) used simulation modelling to evaluate the impacts of mean recruitment regime shift on a stock with productivity dynamics based on the SNA 8 snapper stock.

In addition to the above-mentioned tools, we identified several simple EBFM tools, which can be employed to progress EBFM in jurisdictions with varying levels of fisheries data and political willingness and that show promise for application in New Zealand. These simple EBFM tools include: (i) indicators of ecosystem overfishing (Link and Watson, 2019); (ii) cumulative biomass versus trophic level (Libralato et al., 2019); (iii) PCAs and heatmaps (Karnauskas et al., 2015); (iv) risk tables (Dorn and Zador, 2020); (v) size spectra (Gislason and Rice, 1998; Shin et al., 2005); (vi) hub species (Fulton and Sainsbury, 2024); (vii) the “green band” approach (Lenfest Ocean Program, 2024); (viii) the ecosystem traits index (Fulton and Sainsbury, 2025); and (ix) the indicator species-based approach (Newman et al., 2018) (Appendix A5).

3.2. Ecosystem models

Ecosystem models can be categorised based on their structure as (O’Farrell et al., 2017): (i) conceptual, qualitative and dynamic structural equation models; (ii) extensions of single-species models; (iii) dynamic multispecies models; (iv) aggregated (or whole ecosystem) models; (v) biogeochemical-based end-to-end models; and (vi) coupled and hybrid model platforms. The six categories of ecosystem models have already been employed in New Zealand, albeit only to a relatively limited degree (Table 2 and Appendix A5).

Conceptual models (Kelble et al., 2013), qualitative models (loop analysis; Dambacher, 2001; Dambacher et al., 2003), Bayesian networks (Parsons et al., 2021) and dynamic structural equation models (DSEMs; Thorson et al., 2024) are the simplest forms of ecosystem models. They usually represent good starting points before more complex EBFM research is conducted. For example, conceptual and qualitative modelling constitute ideal preliminary work in preparation for quantitative ecosystem modelling with platforms such as Atlantis (Fulton et al., 2011). DSEMs are a very recent promising tool that can accommodate a combination of lagged and simultaneous impacts of any variable on any other variable and estimate missing values within ecosystem component time series (Thorson et al., 2024; Czaja et al., 2026). This tool remains to be explored in New Zealand.

Extensions of single-species models are models that add additional features (e.g., the influence of abiotic environmental variables or

Table 2
Ecosystem models developed for New Zealand regions.

Ecosystem model category	Ecosystem model name	Modelled region	Reference(s)
Conceptual, qualitative and dynamic structural equation models	Conceptual model	Whangārei region	Darren Parsons, Earth Sciences New Zealand, pers. comm.
	Qualitative model (loop analysis)	Whangārei region	Vidette McGregor-Tiatia, Earth Sciences New Zealand, pers. comm.
	Bayesian network	Hauraki Gulf	Parsons et al. (2021)
	Bayesian network	Tasman Bay/Golden Bay	Jeremy McKenzie, Earth Sciences New Zealand, pers. comm.
	Bayesian network	Part of east Northland (Ngunguru)	Georgina Flowers, Revive Our Gulf, pers. comm.
Extensions of single-species models	C++ Agent Based Model (CABM)	Chatham Rise	Marsh (2022)
Dynamic multispecies models	Multi-species agent-based model	Tasman Bay/Golden Bay	Allison (2022)
	Model of Intermediate Complexity for Ecosystem assessments (MICE model)	Chatham Rise	Matthew Dunn, Earth Sciences New Zealand, pers. comm.
Aggregated (or whole ecosystem) models	Ecopath model	Subantarctic waters over the Southern Plateau	Bradford-Grieve et al. (2003)
	Ecopath with Ecosim (EwE) model	Wellington south coast	Cornwall and Eddy (2015); Eddy et al. (2015)
	Ecopath with Ecosim (EwE) model	Tasman Bay/Golden Bay	McGregor et al. (2021)
	Energy flow (mass balance) model	Te Tapuwae o Rongokako marine reserve	Pinkerton et al. (2008)
	Energy flow (mass balance) model	Chatham Rise	Pinkerton (2011)
	Energy flow (mass balance) model	Hauraki Gulf	Pinkerton et al. (2015)
Biogeochemical-based end-to-end models	Atlantis model	Chatham Rise	McGregor et al. (2019a), (2019b), (2020)
	Atlantis model	Tasman Bay/Golden Bay	McGregor et al. (2021)
Coupled and hybrid model platform	Multispecies size spectrum model	Tasman Bay/Golden Bay	McGregor et al. (2021); Datta et al. (2024)
	Multispecies size spectrum model	Chatham Rise	Datta et al. (2024)
	Multispecies size spectrum model	Poor Knights	Beran et al. (2025)

predation) to existing population models. They include extensions of single-species assessment models and extensions of single-species individual-based models. An extension of a single-species individual-based model called the "C++ Agent Based Model" was developed and utilised for hoki (*Macruronus novaezelandiae*) on the Chatham Rise (Marsh, 2022).

Dynamic multispecies models are ecosystem models which represent a restricted number of stocks that are expected to display large interactions with some stocks of primary interest. Their motivations are investigating the impacts of trophic or technical interactions. Although there have been dynamic multispecies modelling efforts in New Zealand, they have all been pilot studies or uncompleted efforts (Allison, 2022; Mormede et al., 2014; Matt Dunn, Earth Sciences New Zealand, pers. comm.). Among dynamic multispecies models, the ISIS-Fish modelling platform (Mahévas and Pelletier, 2004; Pelletier et al., 2009) is particularly relevant for EAFM in New Zealand, as this modelling platform was specifically designed to explore the dynamics of mixed fisheries. Even more relevant for EAFM in New Zealand are Models of Intermediate Complexity for Ecosystem assessments or "MICE models" (Plagányi et al., 2014). MICE models combine the detailed functionalities of single-species models and the capability to leverage statistical methods to estimate parameters with broader considerations of the studied ecosystem, based on the interests and inputs of resource managers and stakeholders (Plagányi et al., 2014).

Aggregated (or whole ecosystem) models seek to represent all trophic levels within the ecosystem of interest to investigate flows of energy among the components of the ecosystem. They generally simulate the dynamics of a very large number of functional groups and species. Examples of aggregated (or whole ecosystem) models include Ecopath with Ecosim (EwE) models (e.g., Eddy et al. 2015's EwE model for Wellington south coast) and the energy flow model of Pinkerton et al. (2015) for the Hauraki Gulf.

Biogeochemical-based end-to-end models represent both top-down and bottom-up interactions within the ecosystem of interest through the consideration of numerous ecosystem components encompassing fishes, other top predators, planktonic groups, and nutrient components. A widely utilised biogeochemical-based end-to-end modelling platform is Atlantis, a three-dimensional, dynamic modelling platform comprising numerous sub-models which simulate physical and biophysical features, food-web interactions, habitat dependence, biochemical processes, and fisheries (Fulton et al., 2011). In New Zealand, Atlantis models were developed for the Chatham Rise (McGregor et al., 2019a, 2019b, 2020) and TBGB (McGregor et al., 2021).

Finally, coupled and hybrid model platforms are ecosystem models which represent both top-down and bottom-up interactions via the combination or coupling of several model platforms. Popular coupled and hybrid model platforms are the multispecies size-spectrum models (MSSMs) implemented using *mizer*, a freely available R package, which combine the simulated dynamics of several fish species and species groups with those of a resource spectrum representing plankton (Blanchard et al., 2014; Scott et al., 2014). In New Zealand, MSSMs were developed for TBGB (McGregor et al., 2021; Datta et al., 2024), the Chatham Rise (Datta et al., 2024), and the Poor Knights ecosystem, located off the Whangārei region (Beran et al., 2025).

3.3. EBFM tools most relevant for EAFM in New Zealand

Among the EBFM tools reviewed previously (Sections 3.1 and 3.2), we identified those that were currently suitable for EAFM in New Zealand, particularly if the focus of research and management is on technical interactions. For example, the complexity of sophisticated ecosystem models such as EwE and Atlantis models and MSSMs is not required currently for EAFM in New Zealand, especially given capability constraints (Appendix A5). Of the remaining tools, we compiled a comprehensive description of their outputs/questions answered, requirements, use (or absence of use) in New Zealand, and limitations (given the current constraints we describe) to operationalisation in fisheries management (Table 3). It is important to note that these tools also come with other limitations and assumptions that need consideration (Table 4).

Among the tools that we listed for EAFM in New Zealand, métier analysis was given a very high rank, primarily because of its focus on technical interactions. Métier analysis is an important building-block needed to obtain catchabilities required by other EAFM tools that we listed (mixed fisheries forecasts and ISIS-Fish models). However, métier analysis can be useful in itself, for example to characterise a fishery or an ecosystem, and as a sensible unit of action for implementation of EAFM-associated management interventions. In New Zealand, métier analysis of fisheries has recently been recommended to improve the reporting of environmental and ecosystem information for Fisheries New Zealand, with preliminary work done by Middleton et al. (2024). Successful métier analysis in New Zealand will require strategic funding over several years and solid planning for engagement with resource managers and stakeholders, and further developments.

PCAs and heatmaps (some of the simple EBFM tools listed in Section 3.1), were also given a very high rank and, in contrast to métier analysis, take minimal time to develop to provide a characterisation of a fishery or an ecosystem (Section 2.4). As such, PCAs and heatmaps can be given priority over métier analysis, as was done in our FMA 7 case study (Section 3.4). PCAs and heatmaps belong to the tools used by the Lenfest Ocean Program, an international programme aiming to improve ocean research and its communication, particularly to help resource managers transition from single-species management to EBFM (Lenfest Ocean Program, 2024). The Lenfest Ocean Program identified PCAs and heatmaps as practical means to identify and straightforwardly explain key changes in an ecosystem and relate these changes to environmental information, management interventions, and qualitative knowledge. PCAs and heatmaps were recently employed in a large international project using catch data from regional fisheries management bodies and for individual large marine ecosystems (Fulton et al., 2021).

We determined that qualitative models (loop analysis), DSEMs and ISIS-Fish and MICE models (two forms of dynamic multispecies models) are suitable ecosystem models to assist EAFM in New Zealand, primarily because of their more limited data requirements and because these models are simple (or relatively simple) and conducive to collaborative research with resource managers and stakeholders. However, all these ecosystem modelling approaches are still at their infancy, or untried, in New Zealand. Specifically, DSEMs have not been explored in New Zealand yet and one first-cut qualitative model was developed for the Whangārei region (Vidette McGregor-Tiatia, Earth Sciences New Zealand, pers. comm.), while MICE modelling efforts for hoki and southern hake (*Merluccius australis*) on the Chatham Rise have never been completed (Matthew Dunn, Earth Sciences New Zealand, pers. comm.). All existing efforts were supported by internal institutional funding. As is the case for métier analysis, successful ecosystem modelling to assist EAFM will require strategic funding over several years and solid planning for engagement with resource managers and stakeholders, and further developments. This is particularly true for MICE models. There is also very limited expertise with qualitative models (loop analysis), DSEMs and MICE models in New Zealand, which highlights the need to invest in training in the use of these tools, e.g., through training workshops supervised by international experts or scholarships in quantitative modelling for postgraduate students.

We also assigned a high rank to indicators of ecosystem overfishing, cumulative biomass versus trophic level and risk tables, mainly for their simplicity and low data requirements. These approaches are easy to develop and communicate and also belong to the tools identified by the Lenfest Ocean Program to provide a clear big picture of ecosystems in support of EAFM/EBFM (Lenfest Ocean Program, 2024). The MixME method for mixed fisheries forecasts is more complex and has larger data requirements and would involve more substantial funding and training to be employed in New Zealand. Therefore, the MixME method for

Table 3
Tools identified for an ecosystem approach to fisheries management (EAFM) in New Zealand. These tools were qualitatively ranked (assigned a low, medium, high, or very high rank) based on: (i) the questions they can answer/their outputs, considering the current importance of the questions that can be answered to fisheries management in New Zealand; (ii) the requirements of the tools; (iii) their advantages and limitations; and (iv) the resources available in New Zealand to apply them (funding and expertise). Ranks are indicated in the first column.

Tool	Outputs/questions answered	Data/information requirements	Has been used in New Zealand?	Limitations to operationalisation in New Zealand's fisheries management
Métier analysis – Very high rank	• Generate catchability estimates for other EAFM tools, including mixed fisheries forecasts and ecosystem models such as ISIS-Fish models • Can provide a baseline to monitor and assess how métiers may respond to future changes in regulations and policies and other changes • Provides a framework for further analyses of impacts on non-target species and other ecosystem components • Can provide information for research focusing on individual stocks or for conducting fisheries or ecosystem characterisations	• Fisheries catch and effort data (logbook data), catch composition data or observer data, and associated catchability information • Possibly qualitative data obtained from fishers for validation • Expertise with the treatment of large volumes of fisheries catch and effort data, catch composition data or observer data • Expertise with ordination techniques (e.g., principal component analysis (PCA))	Yes, to a very limited extent: some preliminary work was done in Middleton et al. (2024)	• Applications to New Zealand stocks are still to be completed (beyond existing preliminary applications) • Contrary to methods that provide similar insights (PCAs and heatmaps), métier analysis needs to cover a limited number of years where changes in the region of interest (e.g., in terms of regulations or climate) were not substantial
Mixed fisheries forecasts using the Fcube (Fleet and Fisheries Forecast) method – Low rank	• Delivers insights into the impacts of changes in catch and effort for métiers while providing a clear relationship between fishing effort and fishing mortality for different stocks • Calculates fishing mortalities for multiple stocks (based on alternative assumptions about what is driving the overall effort) and then explores scenarios • Can produce results to be compared with those from single-species assessment models, to support fisheries management accounting for technical interactions	• Fully quantitative age-structured single-species stock assessments and the datasets that these stock assessments rely upon • Supplementary data that feed into single-species stock assessments, e.g., discards at the level of métiers and effort and landings values for each of the disaggregated fleets and métiers • Expertise in fisheries forecasts	No	• Fully quantitative age-structured single-species stock assessments are needed for this method, but there are only a few fully quantitative single-species stock assessments in New Zealand • This method requires a lot of data, which are available for some New Zealand regions but involve extensive cleaning and processing • The Fcube method assumes a selectivity pattern that applies to all fleets. • A lot of processing is needed prior to the use of the method because the many data that are required need to be converted into a common structure • Substantial training of New Zealand fisheries modellers would be needed to apply the method in New Zealand
Mixed fisheries forecasts using the FLBEIA (Bio-Economic Impact Assessment using FLR) method – Low rank	• Similar outputs as the Fcube method but in a management strategy evaluation (MSE) framework structure • Outputs can have a more economic focus compared to the Fcube method (e.g., indicate how fishery profits may be maximised) • Can produce results to be compared with those from single-species assessment models, to support fisheries management accounting for technical interactions	• Fully quantitative age-structured single-species stock assessments or biomass dynamic models, and the datasets that these stock assessments rely upon • Supplementary data that feed into single-species stock assessments, e.g., discards at the level of métiers and effort and landings values for each of the disaggregated fleets and métiers • Expertise in fisheries forecasts	No	• Fully quantitative single-species stock assessments are needed for this method, but there are only a few fully quantitative single-species stock assessments in New Zealand • This method requires a lot of data, which are available for some New Zealand regions but involve extensive cleaning and processing • The FLBEIA method employs the Cobb-Douglas catch production function, which represents a simplification of the fisheries catch process compared to the Baranov approach • A lot of processing is needed prior to the use of the method because the many data that are required need to be converted into a common structure • Substantial training of New Zealand fisheries modellers would be needed to apply the method in New Zealand
Mixed fisheries forecasts using the MixME (Mixed-fishery Multi-stock	• Similar outputs as the Fcube method but in an MSE framework structure • Provides insights into the performance of different	• Fully quantitative age-structured single-species stock assessments and the datasets that these stock assessments rely upon	No	• Fully quantitative single-species stock assessments are needed for this method, but there are only a few fully quantitative single-

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Table 3 (*continued*)

Tool	Outputs/questions answered	Data/information requirements	Has been used in New Zealand?	Limitations to operationalisation in New Zealand's fisheries management
Evaluation) method – Medium rank	management rules that better account for technical interactions and identify spaces within trade-offs that meet objectives • Identification of choke species and risks of underutilisation of stocks • Can produce results to be compared with those from single-species assessment models, to support fisheries management accounting for technical interactions	• Supplementary data that feed into single-species stock assessments, e.g., discards at the level of métiers and effort and landings values for each of the disaggregated fleets and métiers • Expertise in fisheries forecasts		species stock assessments in New Zealand • This method requires a lot of data, which are available for some New Zealand regions but involve extensive cleaning and processing • A lot of processing is needed prior to the use of the method because the many data that are required need to be converted into a common structure • Substantial training of New Zealand fisheries modellers would be needed to apply the method in New Zealand
Qualitative models (loop analysis) – Medium rank	• Integration of knowledge about the most relevant components of the ecosystem/region of interest • Exploration of multiple scenarios without the need for a lot of parameterisation • Very often a tool for collaborative work that is more conducive to buy-in of the research produced • Can be extended into Bayesian networks	• Their potential is limited to providing qualitative or semi-quantitative insights into the potential impacts of management measures, which are not always sufficient • Expertise to build and analyse signed digraphs is very limited in New Zealand	Yes, to a very limited extent: a qualitative model is being developed for the Whangārei region (Vidette McGregor-Tiatia, Earth Sciences New Zealand, pers. comm.)	• Their potential is limited to providing qualitative or semi-quantitative insights into the potential impacts of management measures, which are not always sufficient • Expertise to build and analyse signed digraphs is very limited in New Zealand
Dynamic structural equation models (DSEMs) – Medium rank	• Confrontation of conceptual models (different views of the world from scientists, resource managers and stakeholders) with time series data, making them useful for collaborative research and buy-in, particularly at the scoping stage of EAFM projects • Insights into the significance of lagged and simultaneous impacts of any variable on any other variable, and extrapolations of time series • Better understanding of how ecosystem components impact one another, thereby facilitating research investigations with more sophisticated models, including more complex ecosystem models	• Multiple timeseries datasets, such as indices of relative abundances for individual species and/or functional groups, annual environmental indices (e.g., El Niño-Southern Oscillation) and annual fishing mortality rates or fisheries catches for individual species • Some expertise in timeseries analysis in the R programming environment	No	• There is currently limited capacity to develop and run DSEMs in New Zealand
ISIS-Fish models – Low rank	• Investigations of research questions around technical interactions • Evaluation of different types of management measures, alone or in combination (e.g., total allowable catches, fishing effort management measures, restrictions on fishing gears, spatial management measures) • Investigations of multiple processes (e.g., recruitment in relation to reproductive capacity, selectivities for different fishing gears)	• Expertise with multispecies simulation models and the Java programming language • A lot of data and information, including data for stock assessments but also a lot of data and information to parameterise processes such as spatial distributions and reproduction	No	• There is currently no capacity to develop and run ISIS-Fish models in New Zealand • ISIS-Fish is coded in the JAVA programming language which is not as commonly used in New Zealand as C++ • ISIS-Fish models and scenarios are data hungry
Models of Intermediate Complexity for Ecosystem assessments (MICE models) – Medium rank	• Outputs similar to those from single-species models of relative simplicity but also considering broader system considerations that depend on the management objectives being addressed • Outputs directly answering the key questions that resource managers and other stakeholders have and capturing these key questions in the modelling through appropriate formulations, estimating key parameters, and considering important sources of uncertainty	• Solid experience in modelling and capacity to design models to respond to very specific questions • Very often single-species stock assessments, which the MICE models can build upon • Data requirements vary, but MICE models tend not to be data hungry	Yes, to a very limited extent: a MICE model was developed for hoki and southern hake on the Chatham Rise but was never completed (Matthew Dunn, Earth Sciences New Zealand, pers. comm.)	• MICE models are harder to develop than the models that employ the popular Ecopath with Ecosim (EwE) platform • Usually, MICE models are not available in the form of a package and need to be written specifically • There is currently limited capacity to develop and run MICE models in New Zealand, and significant training would be needed for New Zealand modellers to upskill in MICE modelling

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Table 3 (*continued*)

Tool	Outputs/questions answered	Data/information requirements	Has been used in New Zealand?	Limitations to operationalisation in New Zealand's fisheries management
	(which is something that is simply impossible to do with many of the more complex ecosystem models such as EwE or Atlantis) • Are much more likely to produce outputs that will be used in tactical fisheries management compared to more complex ecosystem models, because of their focused and thorough attention to very specific questions • Can be employed in a stepwise approach where they can be quite easily modified to address other very specific questions for the region of interest • Can compute multispecies reference levels and the impacts and uncertainties, while focusing on key species • Can produce risk metrics and be used as operating models within an MSE framework			
Indicators of ecosystem overfishing – High rank	• Insights into whether ecosystem overfishing is taking place in the region of interest or not	• Readily available catch and satellite data	No	• Indicators of ecosystem overfishing are more tools for strategic ecosystem-based fisheries management (EBFM) than tools for tactical EAFM (yet are useful in the toolbox identified for EAFM in New Zealand)
Cumulative biomass versus trophic level – High rank	• Insights into the state of the ecosystem of interest	• Readily available data, including: landing data by species, and trophic levels by species that are easily obtained through FishBase and SeaLifeBase	No	• Cumulative biomass versus trophic level is more of a tool for strategic EBFM than a tool for tactical EAFM (yet is useful in the toolbox identified for EAFM in New Zealand)
Principal component analyses (PCAs) and heatmaps – Very high rank	• Understanding of the ecosystem of interest through the composition of the catch, particularly in mixed fisheries • Tools involving resource managers and stakeholders in identifying major gear shifts, management shifts and/or environmental shifts to facilitate the interpretation of the heatmap, thereby encouraging collaborative work and increasing buy-in of the research produced	• Catch per species over time (e.g., annual landings per species) for a large region (e.g., a fisheries management area)	No	
Risk tables – High rank	• Transparent documentation of concerns to resource managers and other stakeholders • Integration of additional information into stock assessments and fisheries management processes	• Multiple pieces of information at the stock and community levels and the levels of the environment and the ecosystem, coming from different sources such as stock assessments, ecosystem models, and expert knowledge	No	• Risk tables provide qualitative rather than quantitative information

mixed fisheries forecasts was given a medium rank.

3.4. Application of PCAs and heatmaps to FMA 7 landing composition data

We conducted PCAs using landing composition data for FMA 7. The first two PCs together described more than 50% of the variance in the landing composition data (57.91%; PC1: 42.77%; PC2: 15.14%; Fig. A6). Therefore, the first two PCs, and associated biplots, offered a good representation of the landing composition data.

PC1 had a strong positive correlation with year, as well as with several stocks displaying overall increasing landings over the study period: snapper; red gurnard; John dory (*Zeus faber*); elephant fish (*Callorhinchus milii*); and rig (*Mustelus lenticulatus*) (Fig. 2 and Fig. A7). Conversely, PC1 had a strong negative correlation with stocks exhibiting overall decreasing landings over the study period: red cod (*Pseudophycis bachus*); sea perch (*Helicolenus barathri*); and spiny dogfish (*Squalus acanthias*). Therefore, PC1 can be interpreted as the direction of overall changes in landings. The fact that year was the variable with the strongest positive loading on PC1 indicated that the overall landings of the FMA 7 mixed bottom trawl fishery tended to increase in 1992–2024 (Fig. 2 and Fig. A7).

PC2 had: (i) a strong positive correlation with barracouta and rough skate, whose landings in 1992–2024 displayed a bell shape pattern with a peak in 2010; and (ii) a strong negative correlation with blue warehou (*Seriolella brama*), whose landings were at their lowest in 2010 (Fig. 2 and Fig. A7). Thus, PC2 can be interpreted as the magnitude of landing in 2010.

The singular value decomposition PCA identified four natural clusters of years in landing composition, which followed some chronological

Table 4
Assumptions and other limitations of the tools listed in Table 3. More details can be found in Appendix A5.

Tool	Assumptions and other limitations
Métier analysis	• Métier analyses commonly require the use of transformations to normalise the data • Métier analysis requires the number of métiers (“k parameter”) as an input, obtained, e.g., using experts’ opinion or the silhouette width method • Métier analysis requires the selection of a clustering algorithm, which comes with potential limitations (sensitivity to outliers and/or computational costs) • Métier analysis requires (a) feature (variable) selection method(s), which comes with potential drawbacks (e.g., loss of information) • Métier analysis requires the use of (a) method(s) to validate identified clusters, which comes with potential issues (e.g., validation by experts can be biased) • Métier analyses as broadly implemented completely ignore the human behaviours underlying fisheries and the fact that individual fishing vessels represent a critical input to production, which can lead to unrealistic assumptions on fishing effort distribution and métier dynamics • The development of métier analysis takes much more time than the development of methods that provide similar insights (principal component analyses (PCAs) and heatmaps)
Mixed fisheries forecasts using the Fcube (Fleet and Fisheries Forecast) method	• With the Fcube method, it is necessary to make assumptions on the share of the fishing effort among the métiers and the catchability in the following year to be able to determine a multiplier of fishing mortality that is required for the individual stocks • The Fcube method requires assumptions about individual fishing quotas (ITQs) for the fleets, which translate into partial fishing mortality share • Required assumptions on catchability generally result in highly uncertain forecasts • There is no package or documentation for the Fcube method and there is a lack of consistency among the R scripts that have been written for the different existing Fcube applications • Stakeholders pointed to a lack of flexibility in the method to account for changes in behaviour and adaptation to quotas • The method comes with concerns about “weak” or “false” interactions leading to severe choking of target stocks • The Fcube method is less advanced than the FLBEIA and MixME methods and tends to be phased out at present
Mixed fisheries forecasts using the FLBEIA (Bio-Economic Impact Assessment using FLR) method	• The FLBEIA method entails making similar assumptions as with the Fcube method to determine levels of fishing effort required and how fishing effort needs to be distributed among métiers, but also additional assumptions (e.g., environmental influences on recruitment) • Stakeholders pointed to a lack of flexibility in the method to account for changes in behaviour and adaptation to quotas • The method comes with concerns about “weak” or “false” interactions leading to severe choking of target stocks • Required assumptions on catchability generally result in highly uncertain forecasts
Mixed fisheries forecasts using the MixME (Mixed-fishery Multi-stock Evaluation) method	• The MixME method employs multi-fleet Baranov catch equations to model fisheries catches • The MixME method does not have a fleet or a métier structure but rather considers hybrid fishing units • Required assumptions on catchability generally result in highly uncertain forecasts • Stakeholders pointed to a lack of flexibility in the method to account for changes in behaviour and adaptation to quotas • The method comes with concerns about “weak” or “false” interactions leading to severe choking of target stocks
Qualitative models (loop analysis)	• Qualitative models are steady-state, strategic models • With loop analysis, only positive and negative impacts are considered and there is no quantification of strength of relationships among variables
Dynamic structural equation models (DSEMs)	• DSEMs can represent only a limited number of (simultaneous and lagged) relationships among variables, otherwise they quickly become overfitted • DSEMs can only specify linear relationships among variables
ISIS-Fish models	• ISIS-Fish models require assumptions to be made about management measures and fishers’ responses to these management measures and economic and environmental conditions, via an interactive script editor
Models of Intermediate Complexity for Ecosystem assessments (MICE models)	• The general MICE philosophy is to simplify the study ecosystem using mathematical relationships as a proxy for more complex processes • MICE models cover a wide range of models but usually require many assumptions to be made about processes and parameters (in the absence of data or publications in the literature). As such, MICE modelling studies very often resort to an ensemble of model formulations with different equations, different fitting scenarios, and different ways to account for uncertainty
Indicators of ecosystem overfishing	• There are three types of indices of ecosystem overfishing (the Ryther index, the Fogarty index, and the Friedland index), which come with limitations. For example, the Friedland index is obtained by dividing catches by chlorophyll-a concentration for the ecosystem of interest, thereby ignoring some sources of primary productivity such as kelps and microphytobenthos • Indices of ecosystem overfishing need to be associated with specific threshold to help determine whether ecosystem overfishing is taking place in the region of interest or not
Cumulative biomass versus trophic level	• This method assumes a S-shaped relationship between trophic level and cumulative biomass to determine the state of the ecosystem of interest (degraded, healthy, or recovering); the shape of the S-shaped relationship is very responsive and the point of inflexion of

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Table 4 (*continued*)

Tool	Assumptions and other limitations
	the S-shaped curve is a very sensitive indicator to track ecosystem state
Principal component analyses (PCAs) and heatmaps	• Heatmaps are mainly a graphical representation of changes in the study ecosystem, not a method to investigate these changes • Multinormality is assumed with PCAs. Non-independence in time between observations (i.e., temporal autocorrelation) is problematic when the primary objective of PCAs is inferential, and it may also affect the descriptive ability of PCAs • Stationarity (i.e., the absence of trends in the data) is also assumed with PCAs. Stationarity may affect PCAs when their primary objective is inferential or descriptive • Because the assumptions of absences of temporal correlation and trends are strong, it is good practice to assume that the variance patterns predicted by PCAs could have emerged by chance and examine (e.g., using statistical tests) whether this assumption can be rejected • It is not possible to attribute the associations between time series displayed by graph of variables to causal relationships, because associations between time series may very often merely stem from the fact that the time series show quasi monotonic trends over the long term
Risk tables	• Risk tables employ a scoring system to assess how severe concerns are, which can potentially be subject to biases (e.g., if it relies too heavily on expert knowledge)

order (Fig. 3). Cluster 1 included the first years (1992–1995) and 2002–2006 and was negatively correlated with PC1 and spanned both the positive and negative values of PC2. Cluster 2 encompassed the second period of the time series (1996–2001) and was negatively correlated with both PC1 and PC2. Cluster 3 included 2007–2018 and was mostly positively correlated with PC1 and positively correlated with PC2. Finally, Cluster 4 encompassed the last period of the time series (2019–2024) and was positively correlated with PC1 and negatively correlated with PC2 (Fig. 3). Hierarchical clustering of the scores per stocks against the PCs resulted in four similar clusters (Fig. S8). The year 2024 was most positively correlated with PC1, while 1996–1998 were most negatively correlated with PC1 (Fig. 3). Given the interpretation that can be made of PC1, the results of the singular value decomposition PCA reinforce the idea that the overall landings of the FMA 7 mixed bottom trawl fishery tended to increase over the entire study period (1992–2024).

The four clusters identified by the singular value decomposition PCA were apparent on the heatmap (Fig. 4). The first cluster (1992–1995 and 2002–2006) corresponds to a period where flatfishes (Rhombosoleidae spp.) were largely targeted and associated bycatch species were also caught in substantial volumes (e.g., red cod, smooth skate (*Dipturus innominatus*) in 1992–1995) (Doug Saunders-Loder, Talley's Group Limited, pers. comm.). The second cluster (1996–2001) was a period with frequently low contributions to fishery landings for many stocks, including red gurnard, John dory, and rough skate. The third cluster (2007–2018) corresponds to when fisheries data in New Zealand started to be reported at a fine spatial scale but also when sea surface temperature (SST) began to noticeably increase in the FMA 7 region (Grüss et al., 2025). In 2007–2018, landing compositions were particularly high for tarakihi, rough skate, and school shark (*Galeorhinus galeus*). Finally, the fourth cluster (2019–2024) was a period where New Zealand moved to the use of the electronic reporting system for fisheries data whilst fishers changed their behaviour to avoid certain species within the FMA 7 region, especially in relation to the restricted TACC of snapper given its boom in abundance (Langley, 2024). However, the fourth cluster (2019–2024) was also a period where SST and bottom temperature substantially increased and marine heatwaves started to become more regular (Behrens et al., 2025). In 2019–2024, landing compositions were particularly high for snapper and red gurnard, as well as for rig and elephant fish primarily because these two species were increasingly caught as bycatch in tows targeting red gurnard and snapper. (Fisheries New Zealand, 2024). In the third (2007–2018) and fourth (2019–2024) clusters of years, the frequently low contributions to fishery landings for flatfishes and associated bycatch species (e.g., red cod, smooth skate) may be related to loadings of sediment in the FMA 7 region, which started to increase towards the mid−2000's (Doug Saunders-Loder, Talley's Group Limited, pers. comm.).

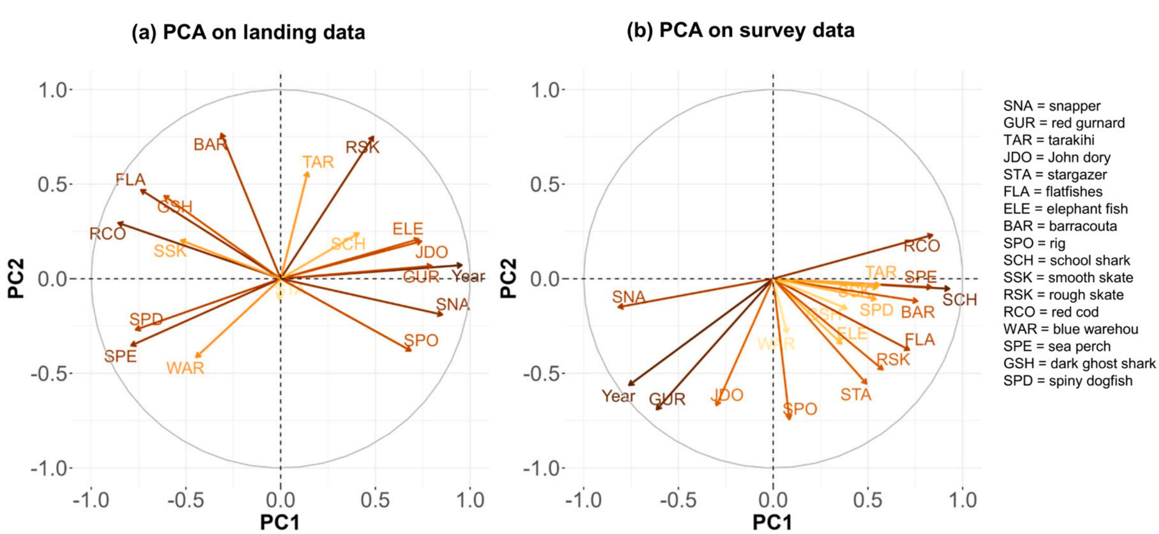

Fig. 2. Graphs of variables, showing the contribution of each variable (fisheries management area 7 (FMA 7) stocks and fishing year) to the first two principal components (PCs) in the spectral decomposition principal component analysis (PCA) on: (a) commercial bottom trawl landing composition data; and (b) bottom trawl research survey relative biomass data.

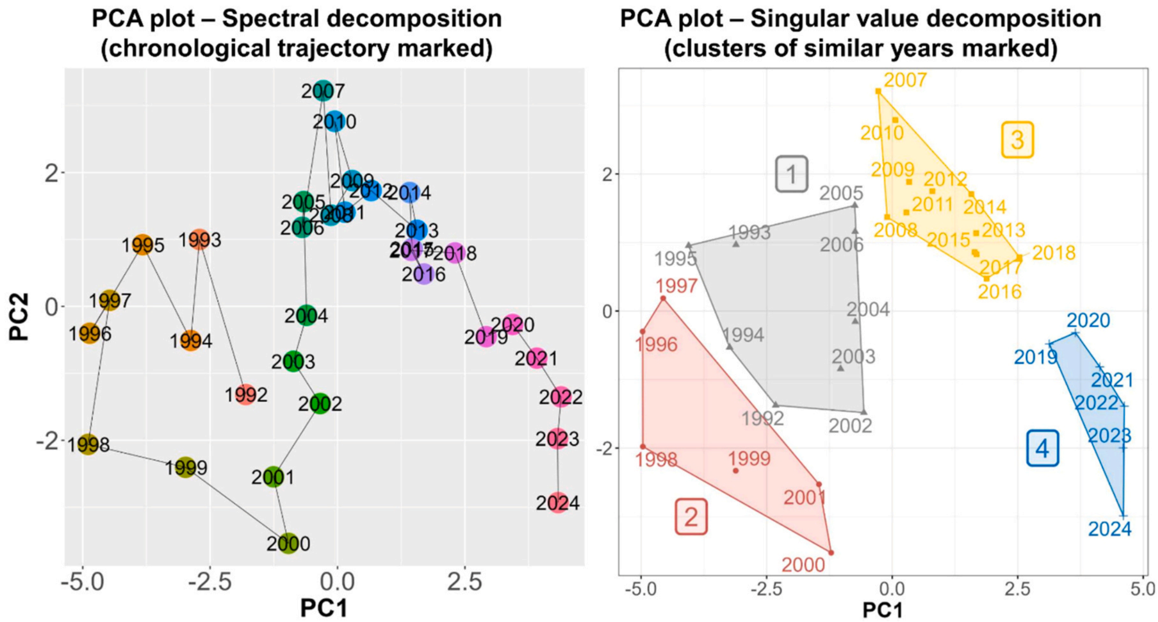

Fig. 3. Two-dimensional principal component analysis (PCA) plots for the PCAs on commercial bottom trawl landing composition data for fisheries management area 7 (FMA 7) stocks: (a) spectral decomposition PCA; and (b) singular value decomposition PCA. The time trajectory in the spectral decomposition PCA begins with red dots in fishing year 1992 moving through the rainbow to pink in fishing year 2024. In the singular decomposition PCA, clusters of similar fishing years are marked and numbered.

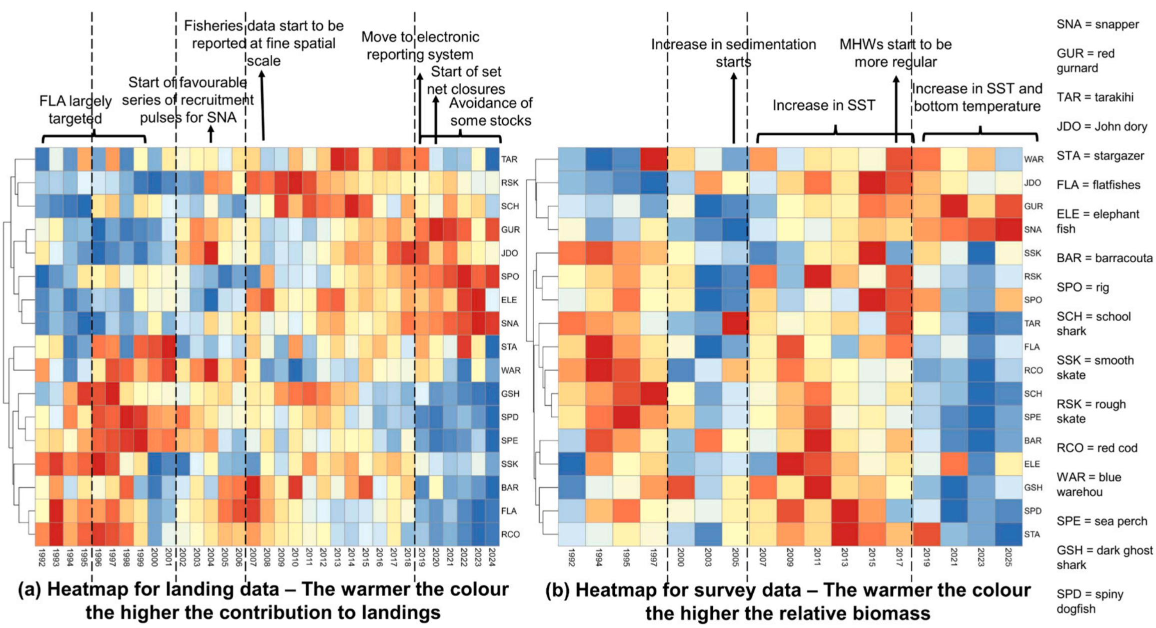

Fig. 4. Heatmaps for the individual contributions of fisheries management area 7 (FMA 7) stocks to (a) commercial bottom trawl landing compositions through time and (b) bottom trawl research survey relative biomasses through time, created by ranking the landings or relative biomasses per individual stocks through time. Stocks with similar patterns through time are grouped together. Heatmaps are annotated based on consultations of the literature, fisheries managers and fishing industry representatives, to indicate important environmental and management events in FMA 7. Vertical dashed black lines indicate where principal component analysis clusters of years (Fig. 3 for the left panel and Fig. 5 for the right panel) broke out. SST = sea surface temperature; MHWs = marine heatwaves.

3.5. Application of PCAs and heatmaps to FMA 7 survey relative biomass data

We also used relative biomass data for FMA 7 from fisheries-independent surveys to carry out PCAs and generate a heatmap, to better infer whether the changes found with landing composition data arose from ecological or environmental shifts or changes related to fishing or resource management (Figs. 2 and 4–5 and Figs. A6 and A8). Here, the first two PCs together described more than 50% of the variance in the survey relative biomass data (53.75%; PC1: 38.13%; PC2: 15.62%) and, therefore, offered a good representation of these data (Fig. A6).

PC1 had a strong positive correlation with several stocks displaying overall decreasing relative biomasses over the study period: school shark; red cod; and sea perch (Fig. 2 and Fig. A9). Conversely, PC1 had a strong negative correlation with: (i) snapper and red gurnard, whose relative biomasses increased overall over the study period; and (ii) John dory, whose annual relative biomass exhibited a dome shape pattern with a peak in around 2015 (Fig. 2 and Fig. A9). Therefore, PC1 can be interpreted as the opposite of the direction of overall changes in relative biomasses.

PC2 was hard to interpret. It had a positive correlation with red cod (Fig. 2). It also had a negative correlation with: (i) rig, whose relative biomass fluctuated over time, with a peak in 2015; (ii) red gurnard, whose relative biomass increased markedly starting from 2008 and reached particularly high values in 2015, 2021 and 2025; and (iii) John dory, whose relative biomass reached a peak in 2015 (Fig. 2 and Fig. A9).

The singular value decomposition PCA identified four natural clusters of years in relative biomass, which followed a clear chronological order (Fig. 5). Cluster 1 included the first years of the study period (1992, 1994, 1995, and 1997) and was positively correlated with PC1 and negatively correlated with PC2. Cluster 2 encompassed the second part of the study period (2000, 2003, and 2005) and was most negatively correlated with PC1 and negatively correlated with PC2. Cluster 3 included the third part of the study period (2007, 2009, 2011, 2013, 2015, and 2017) and was most positively correlated with both PC1 and PC2. Finally, Cluster 4 included the last years of the study period (2019, 2021, 2023, and 2025) and was negatively correlated with PC1 and mainly positively correlated with PC2. Hierarchical clustering of the scores per stocks against the PCs resulted in four similar clusters (Fig. A8). The years 1994 and 1995 were most positively correlated with PC1, while 2023 and 2025 were most negatively correlated with PC1 (Fig. 5). Given the interpretation that can be made of PC1, the results of the singular value decomposition PCA suggested that the overall relative biomass of FMA 7 stock complex tended to increase over the period 1992–2025.

The four clusters identified by the singular value decomposition PCA were apparent on the heatmap (Fig. 4). Patterns in relative biomasses on the heatmap for survey data generally concurred well with patterns in landing composition displayed on the heatmap for landing data: (i) the relative biomasses of flatfishes and associated bycatch species (e.g., red cod, smooth skate) were particularly high in 1992–1997; (ii) the relative biomasses of snapper, flatfishes and associated bycatch species, and elephant fish and rig, were particularly low in 2000–2005; (iii) the relative biomasses of tarakihi, rough skate and school shark (as well as those of stargazer (*Kathetostoma giganteum*) and dark ghost shark (*Hydrolagus novaezealandiae*)) were particularly high in 2007–2017; and (iv) the relative biomasses of snapper and red gurnard were particularly high in 2019–2025. Exceptions to this general agreement included elephant fish and school shark in 2019–2025; specifically, the relative biomass of elephant fish and school shark declined overall over the period 2019–2025 compared to the period 2007–2017 (Fig. 4).

4. Discussion

Some countries and regions have reached some of their EBFM ambitions (e.g., in the USA; Harvey et al., 2025) but progress in operationalising EBFM has often been slow or hindered in many places (Levin et al., 2014; Skern-Mauritzen et al., 2016; Cormier et al., 2017). Achieving holistic management that benefits fisheries and entire ecosystems is obviously challenging but has now become even more challenging in the current economically constrained context. For example, budget cuts in the USA recently compromised the ambitious Changing Ecosystem and Fisheries Initiative (CEFI) and the human resources available for EBFM research. In New Zealand, funding for fisheries research has decreased since the 1990s (Mace et al., 2014; Durante et al., 2020) and resources specifically for EBFM have become more limited since the end of the Sustainable Seas National Science Challenge in June 2024. A practical and strategic approach to fulfil the goals and ambitions of EBFM worldwide is, therefore, more relevant now than ever. In the present study, we developed an approach to help consolidate EAFM (ecosystem-based management for a specific fishery) towards EBFM (ecosystem-based management for multiple fisheries) in New Zealand, which we demonstrated through a first application to FMA 7 (which can be followed by other applications with future funding). Our approach, or some aspects of it, can be applied for other case studies worldwide, to put more focus on EAFM, in order to more effectively reach EFBM ambitions.

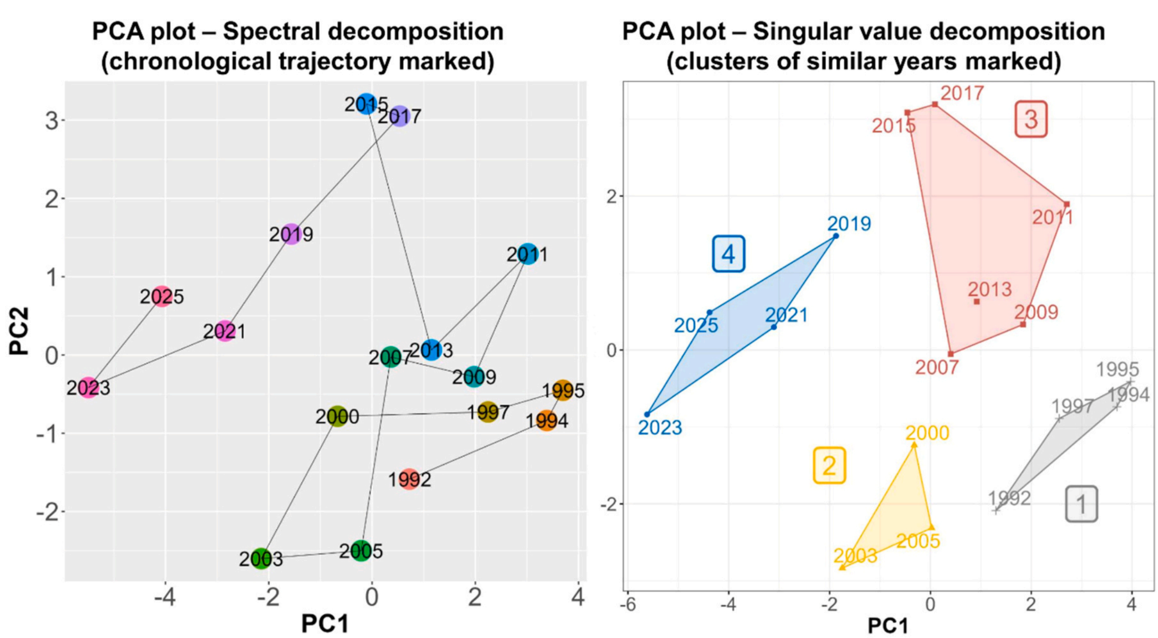

Fig. 5. Two-dimensional principal component analysis (PCA) plots for the PCAs on bottom trawl research survey relative biomasses for fisheries management area 7 (FMA 7) stocks: (a) spectral decomposition PCA; and (b) singular value decomposition PCA. The time trajectory in the spectral decomposition PCA begins with red dots in fishing year 1992 moving through the rainbow to pink in fishing year 2024. In the singular decomposition PCA, clusters of similar fishing years are marked and numbered.

4.1. Tools to progress EAFM

Our approach includes a review of the literature (peer-reviewed articles and technical reports), extensive consultations with resource managers and stakeholders and international experts from the start of the research, and a detailed description of EBFM tools recommended for EAFM. The application of our approach to New Zealand highlighted a hard truth; whilst fisheries represent substantial social, economic and cultural assets for New Zealand (Gerrard, 2021), there are very few EBFM tools recommended for EAFM that the country can afford to implement given the financial and human resources available, at least in the short term. In addition, there is some institutional inertia that impacts EAFM and EBFM advancement, because stocks in New Zealand have been managed using a single-species approach (with additional consideration of environmental interactions) since the introduction of the Quota Management System in 1986, and buy-in from managers and stakeholders on shifts away from this well-accepted scheme to EAFM and EBFM will require time and engagement. Therefore, mixed fisheries forecasts, which are tools allowing for an understanding of the impacts of catch settings for individual stocks on associated species (technical interactions) are of immediate interest for New Zealand. However, fully quantitative stock assessments needed for mixed fisheries forecasts are few in New Zealand, and the amount of data processing and expertise required for mixed fisheries forecasts is also considerable. In addition, most mixed fisheries forecasts rely on métier analysis as a preliminary step, yet métier analysis itself comes with challenges in New Zealand (essentially the time needed to train scientists and develop applications).

The application of our approach to New Zealand also revealed that employing even relatively simple ecosystem modelling tools like qualitative models (loop analysis), DSEMs and MICE models will be difficult in the short term, at least beyond preliminary efforts, as several years of strategic funding and training and engagement with resource managers and stakeholders will be necessary to support their development. This is particularly true for MICE models, which have now become key tools for EAFM, EBFM and EBM internationally (e.g., Punt et al., 2016b; Chagaris et al., 2020; Rogers et al., 2023; Plagányi et al., 2024; Wassermann et al., 2025).

Our approach identified PCAs and heatmaps as some of the tools that can readily be used to assist EAFM in New Zealand. Therefore, we employed PCAs and heatmaps for the FMA 7 mixed bottom trawl fishery case study as a means to produce an "ecosystem characterisation", in lieu of more onerous métier analysis. PCAs and heatmaps proved to be valuable to understand the contribution of species to the catch and how this contribution peaks and changes over time, species groupings through time, and major species shifts in the ecosystem. Consultations with fisheries managers, fishing industry representatives and other stakeholders allow for the interpretation of this ecosystem characterisation in light of changes in the abiotic environment, fishing behaviour or resource management. While these discussions could be replaced by a covariate analysis (e.g. as part of a dynamic factor analysis (DFA); Ward et al., 2022) to identify whether an environment driver was shaping the responses, the act of having the conversations over how the fishery has evolved through time is a useful part of EAFM. As such, PCAs and heatmaps represent valuable tools to support stakeholder/manager discussions around historical changes to the ecosystem underlying a mixed fishery and evaluate ecosystem health relative to historical status to reflect on management measures for that mixed fishery. Collaborative hypothesis generation via the annotation of heatmaps is also an important outcome that can lead to the development of indicators of risk for the mixed fishery of interest (Seara et al., 2024). It is important to note that heatmaps are mainly a graphical representation of changes in the study ecosystem, not a method to investigate these changes (ICES, 2022); as such, we support the combined use of PCAs and heatmaps as opposed to heatmaps alone.

We note that, although the approach reported in the present study is valuable to identify tools to progress EAFM towards EBFM in collaboration with stakeholders and international experts, it can still miss potentially interesting tools. This stems from the fact that EBFM research has been very fruitful worldwide for several decades, so that some relevant international experts are inevitably missed with our approach. For example, we were unable to involve many European experts we contacted in the present study, primarily because of the large time differences between New Zealand and European countries. As such, our list of tools to progress EAFM in New Zealand (Table 3) could have been longer, e.g., could have included DFA (see Section 4.2) and could have addressed some caveats with métier analysis. Métier analyses as broadly implemented completely ignore the human behaviours underlying fisheries and the fact that individual fishing vessels represent a critical input to production, which can lead to unrealistic assumptions on fishing effort distribution and métier dynamics (Schadeberg et al., 2021). Métier analysis represents only a subset of tools that describe joint, or multioutput, production, e.g., integrated multi-species and multi-métier individual-based models (Nielsen et al., 2018).

We also note that our review of the EBFM tools considered in this paper (Appendix A5) was not comprehensive, as this was beyond the scope of the present study (the scope of the present study being an approach to identify tools to progress EAFM towards EBFM in New Zealand and a first application of these tools). For more comprehensive reviews of the EBFM tools considered in the present study, the reader is referred to the publications and reports listed in Table 5, noting that our list of publications and reports in Table 5 is not exhaustive (given how very fruitful EBFM research has been over several decades).

4.2. PCAs and heatmaps versus more sophisticated methods

Following on the points that were made above, we emphasise that, while PCAs and heatmaps were identified for inclusion in the list of tools for EAFM in New Zealand and proved valuable (as highlighted by our application to the FMA 7 case study), other multivariate statistics are relevant for EAFM and may be worth considering in future studies. Below, we discuss the advantages and limitations of PCAs, as well as avenues for future research using DFA (Zuur et al., 2003a, 2003b) and other methods that are more sophisticated than PCAs.

In practical terms, as a rapid means of scanning for underlying structure in the data, the combination of PCAs and heatmaps has wide utility. PCAs and heatmaps do not require specialist standardisation of the data, they are available in many statistical packages, and they are more easily directly interpretable without the requirement for additional processing. PCAs and heatmaps deliver a clear big picture of the ecosystem of interest, which can help fisheries managers make informed decisions. For example, in a resource limited environment, prioritising groups of species or common issues for analysis using PCA and heatmaps, rather than taking every issue one by one, can make better use of resources and give additional insight into synergies or trade-offs between species to provide the most overall benefit. The outputs of PCAs are very easy to communicate to resource managers and stakeholders,

Table 5
Non-exhaustive list of publications and reports reviewing the ecosystem-based fisheries management (EBFM) tools discussed in the present study.

Tool	Publications and reports
Métier analysis	Deporte et al. (2012)
Mixed fisheries forecasts	Aristegui-Ezquibela et al. (2021)
Ecosystem models	Plagányi (2007); O'Farrell et al. (2017); Espinoza-Tenorio et al. (2012)
Models of Intermediate Complexity for Ecosystem assessments (MICE models)	Plagányi et al. (2014)
Management strategy evaluation (MSE)	Punt et al. (2016a,b)
Simple EBFM tools	Lenfest Ocean Program, (2024)
Indicators for EBFM	Jennings (2005); Powers and Monk (2010)
Multivariate statistics for EBFM	ICES (2022)

and resource managers can easily understand them and even implement PCAs themselves without extensive training. While we agree there is value in using methods that can more directly identify driving covariates, and that scientists need to push the boundaries of science to obtain the best possible outputs, we argue that applied science needs to adopt (at least start with) a simpler approach that has an easier uptake, to deliver strong foundations, and build from there for the effective implementation of EAFM, towards EBFM.

All this being said, the assumptions and limitations of PCAs need to be acknowledged, which also points to the consideration of DFA, and other methods that are more sophisticated than PCAs, as potential next steps. First, multinormality (i.e., independence in time between observations) and stationarity (i.e., the absence of trends in the data) are assumed with PCAs (Planque and Arneberg, 2018). Non-independence in time between observations (temporal autocorrelation) is problematic when the primary objective of PCAs is inferential (ICES, 2022; Planque and Arneberg, 2018). Jolliffe (2002) stated that non-independence in time between observations has virtually no impacts when the primary objective of PCAs is descriptive. On the contrary, Vanhatalo and Kulahci (2016) reported that non-independence in time between observations may affect the descriptive ability of PCAs. Stationarity may affect PCAs when their primary objective is inferential or descriptive (Brillinger, 1975). Because the assumptions of absences of temporal correlation and trends are strong, it is good practice to assume that the variance patterns predicted by PCAs could have emerged by chance and examine whether this assumption can be rejected (Planque and Arneberg, 2018). Our heatmaps and chronological clustering could be viewed as confirming our PCA findings, yet we recommend future studies ascertain whether the variance patterns predicted by PCAs did not emerge by chance using appropriate statistical tests. Moreover, it is important to stress that it is not possible to attribute the associations between time series displayed by graph of variables to causal relationships, because associations between time series may very often merely stem from the fact that the time series show quasi monotonic trends over the long term (ICES, 2022).

Given the assumptions and limitations of PCAs detailed above, future research could consider employing: (i) DFA (Zuur et al., 2003a, 2003b) or similar methods (e.g., dynamic-inner principal component analysis; Dong and Qin, 2018; multivariate autoregressive models with trends; ICES, 2022) to address the issues of temporal correlation and trends in the data; and (ii) empirical dynamic models (Sugihara et al., 2012) as plausible models of causality of observed dynamics. DFA are particularly worth highlighting as they can include a linear regression component allowing for the quantification of relationships between pressures (e.g., environmental variables) and states (e.g., fish species landings) through regression parameters. It is then interesting to combine DFA with heatmaps that integrate both pressure and state variables (Karnauskas et al., 2015).

4.3. *PCAs and heatmaps for the FMA 7 case study*

PCAs and heatmaps on landings were particularly valuable for the FMA 7 case study as we were able to supplement the PCAs and heatmap on landing composition data with a second type of PCAs and heatmap on survey relative biomass data. We found that, over the last 34 years, the overall relative biomass and overall landings of the FMA 7 stock complex increased. However, the last 34 years appeared to be divided into four clusters of years, starting with a period where the biomasses and landings of flatfishes and associated bycatch species (e.g., red cod, smooth skate) were particularly high and ending with a period where the biomasses and landings of the commercially valuable snapper and red gurnard stocks increased markedly. Using the literature and knowledge from resource managers and stakeholders, we were able to interpret the clusters of years in light of changes from natural or anthropogenic causes. For example, increased snapper biomass and landings in the most recent years may be partly explained by warming and more regular marine heatwaves that benefited the snapper population (Behrens et al., 2025). Another example are the low biomasses and landings of flatfishes and some of their associated bycatch species in the most recent years of the study period, which fishing industry representatives suggested may be due to enhanced sedimentation within the FMA 7 region (Doug Saunders-Loder, Talley's Group Limited, pers. comm.).

Because research survey data are not available at large spatial and temporal scales and in large quantities for numerous world regions, landings represent an opportunistic source of data for PCAs and heatmaps to investigate changes for multiple species over several decades. However, wherever available, research survey biomass data should also be employed to implement an additional PCA and heatmap output. As landings are generally not considered reliable proxies for changes in biomasses, the use of research survey biomass data helps improve the analyses and validate cases where landings are thought to be good proxies. Our FMA 7 mixed bottom trawl fishery case study was ideal in that research surveys are regularly carried out off the west coast South Island (MacGibbon et al., 2024). Our ability to conduct PCAs and generate heatmaps for the FMA 7 case study using both landing composition and survey biomass data proved to be valuable. For instance, we found that the contributions of rig and elephant fish (two low-value stocks compared to snapper and red gurnard; Fisheries New Zealand, 2019) to landings were particularly high from 2019 onwards, whereas the relative biomasses of the two stocks declined overall in 2019–2025 relative to the previous time period (2007–2017). This finding concurs with some of the results of Durante et al. (2020), who investigated the marine trophic index of landings in New Zealand over time. Durante et al. (2020) found that the landings and biomasses of lower-value species tended to diverge, whilst this was usually not the case for higher-value species. Therefore, we conclude that, if only landing data are available for PCAs and heatmaps, the outcomes of the PCAs and heatmaps for lower-value species should be interpreted with particular care. In addition, resource managers, fishing industry representatives and other stakeholders should be consulted for interpretation of these outcomes.

4.4. *Roadmap to continue progressing EAFM in New Zealand*

Progress towards EBFM is already happening in New Zealand to some degree (see Section 1 and Appendix A1), and the applications of the tools recommended in the present study (Table 3) will help progress EAFM and support current fisheries management efforts in several ways (Appendix A10). In particular, PCAs, heatmaps and métier analysis can contribute to a better framework for defining New Zealand fisheries, by delivering an understanding of catch composition as an emergent property of these fisheries. In turn, enhanced understanding of catch composition in fisheries could help fisheries managers take decisions such as bycatch management measures (e.g., implementing bottom trawl closures in some locations where fishing vessels targeting bony fishes are increasingly catching chondrichthyans as bycatch). Where possible, future studies using PCAs and heatmaps should perform the second type of PCAs and heatmaps on research survey data. Moreover, consultations with international experts highlighted that it is good practice to leverage existing modelling platforms and code bases where possible. Given the restricted resources available in New Zealand, future métier analysis (a tool that was given a very high rank to assist EAFM in New Zealand) could incorporate learnings from previous applications such as efforts for the Australian tuna and billfish fisheries (Parsa et al., 2020a, 2020b) or employ statistical spatio-temporal models for which expertise is available in New Zealand (e.g., Grüss et al., 2023, 2025; Charsley et al., 2025) (Appendix A5).

We also found that, in addition to PCAs, heatmaps and métier analysis, three simple EBFM tools have very good potential to assist EAFM in New Zealand: indicators of ecosystem overfishing (Link and Watson, 2019); cumulative biomass versus trophic level (Libralato et al., 2019); and risk tables (Dorn and Zador, 2020). These three tools were all assigned a high rank, mainly because they do not rely on the outputs of complex ecosystem models (e.g., EwE or Atlantis models or MSSMs). All the above-mentioned EBFM tools can build on one another in a more comprehensive yet still simple approach; for example the PCA or heatmap results could potentially feed into a risk assessment at the ecosystem level, and a risk assessment could lead fisheries managers to prioritise other analyses such as conceptual models and MSE as done in the U.S. Mid Atlantic (DePiper et al., 2021; Muffley et al., 2021). Moreover, while numerous types of multivariate analyses (including sophisticated ones such as DFA and redundancy analysis) have been trialled most typically in research contexts, regular reporting of ecosystem indicators, which are important to resource managers, is still not done routinely in most jurisdictions globally. As such, PCAs and heatmaps, indicators of ecosystem overfishing, cumulative biomass versus trophic level and risk tables (and other indicators identified by the Lenfest Ocean Program; Lenfest Ocean Program, 2024) should be given more consideration worldwide, primarily because they deliver a bigger picture of context for strategic decisions which is understandable by a large audience.

In addition to the use of our approach, we recommend that future efforts in New Zealand continue to improve the incorporation of EBFM into New Zealand's research and management processes. To reach this goal, two recommendations from the international experts that we consulted for the present study are particularly relevant: (i) fitting EBFM tools within assessment and management timelines and cycles; and (ii) making more use of MSE, to evaluate how well fisheries management perform under uncertainty and improve buy-in from resource managers and other stakeholders. The system for peer review that Fisheries New Zealand implements with science working group (WG) meetings will be helpful to address these two recommendations. For example, project leads for future ecosystem modelling projects can take advantage of WG meetings early on in the project to develop and explore conceptual models, qualitative models and/or DSEMs with the WG community before moving to more complex, quantitative ecosystem models. This system will also be advantageous for MSE, with: (i) the development of scenarios and performance metrics with the WG community at early WG meetings; and (ii) the analysis, interpretation and discussion of MSE outcomes with the WG community at later meetings. However, as is the case with other modelling endeavours, consolidated MSE frameworks in New Zealand will necessitate several years of strategic funding and training.

4.5. Concluding remarks

In conclusion, the approach that we developed to guide EBFM via EAFM confirmed a hard truth; in an economically constrained context, financial and human resources for EBFM research are very limited in New Zealand, even to develop relatively simple EAFM tools. The present study can help New Zealand take practical decisions to progress EBFM through strategic funding and capacity building. However, New Zealand is far from being uniquely affected in this way. We believe that virtually all world regions may benefit from the approach presented in this study or some aspects of it, to consolidate EAFM in order to meet the goals and ambitions of EBFM in the longer term. The increasing constraint on funding that has accelerated through the repeated economic, climate and geopolitical shocks of the past two decades has long had conspicuous impacts on EBFM research in many countries (e.g., Greece, Spain) but is now also compromising advances in EBFM research elsewhere, even where notable successes have been achieved previously (i.e., the USA; Harvey et al., 2025). In this context, we recommend that fisheries research and management organisations consider the balance between resources and scope, with the possibility that in the short to medium term efforts may need to focus on building strong foundations for EBFM via the development of robust EAFM tools. The costs and benefits of simple and more sophisticated tools should be carefully factored in, as simple models are more readily affordable but the scope of questions that they can address is more limited, whereas more sophisticated tools cost more but can address more complex questions and have the potential to result in substantially improved resource management and overall outcomes. We hope that the approach that we presented in this study will be useful for these efforts, to reach a win-win-win situation for fisheries, ecosystems, and the workforce available for EBFM research.

CRediT authorship contribution statement

Dambacher Jeffrey: Writing – review & editing, Investigation. **Arnaud Grüss:** Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Dolder Paul:** Writing – review & editing, Investigation. **Mahdi Parsa:** Writing – review & editing, Investigation. **Plagányi Eva:** Writing – review & editing, Investigation. **Keith Sainsbury:** Writing – review & editing, Visualization, Investigation. **Parsons Darren:** Writing – review & editing, Investigation. **Davis Jean:** Writing – review & editing, Resources, Methodology, Investigation. **Fulton Elizabeth:** Writing – review & editing, Visualization, Resources, Methodology, Investigation. **Sean Pascoe:** Writing – review & editing, Investigation. **Vidette McGregor-Tiatia:** Writing – review & editing, Investigation, Funding acquisition. **Blanchard Julia:** Writing – review & editing, Investigation. **Holmes Steven:** Writing – review & editing, Investigation. **Raymond Czaja:** Writing – review & editing, Investigation. **Gaichas Sarah:** Writing – review & editing, Investigation. **Samik Datta:** Writing – review & editing, Visualization, Investigation, Funding acquisition.

Data statement

The commercial landing data employed in the present study are confidential and cannot be shared, while the research survey data used in the present study, which are the property of Fisheries New Zealand, can be obtained via an email to rdm.sharedrdm@mpi.govt.nz.

Funding

This work was supported by Fisheries New Zealand through project INV2023-10 and Earth Sciences New Zealand Strategic Science Investment Funding (SSIF). One of the funders of the present study, Fisheries New Zealand, participated in study design. Otherwise, none of the funders of the present study had any role in data collection and analysis, decision to publish, or preparation of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We thank very much Fisheries New Zealand for providing the data used in the present study, as well as the Fisheries New Zealand-chaired Biodiversity Research Advisory Group (BRAG) for very helpful discussions and feedback on our research. We are also very grateful to the following people for their help or advice at different levels of the present study: Alex Kroch, Marc Griffiths, Ian Tuck, Daniel Heslop, Allen Frazer and Hannah Mello (Fisheries New Zealand), Isaac Kaplan and Howard Townsend (NOAA Fisheries), Paul Burch (CSIRO), Matt Dunn, Matt Pinkerton, Mark Morrison, Jeremy McKenzie and Sira Ballara (Earth Sciences New Zealand), Georgina Flowers (Revive Our Gulf), Doug Saunders-Loder (Talley's Group Limited), Carol Scott (Southern Inshore Fisheries Management Company Ltd), John Willmer (Seafood New Zealand), Eric Jorgensen (Ocean Bay Farms), the BRAG community, and all attendees of the workshops with international experts. We also thank very much internal reviewers (Richard O'Driscoll for Earth Sciences New Zealand, Phil Heath for Fisheries New Zealand, and anonymous scientists from Cefas and the Australian Bureau of Agricultural and Resource Economics), as well as the Fisheries New Zealand RDM Team, for assessing our manuscript. Last but not least, we are very grateful to the Editor (André Punt) and two anonymous reviewers for their insightful and constructive comments which substantially improved our manuscript. This work was supported by Fisheries New Zealand through project INV2023–10 and Earth Sciences New Zealand Strategic Science Investment Funding (SSIF). One of the funders of the present study, Fisheries New Zealand, participated in study design. Otherwise, none of the funders of the present study had any role in data collection and analysis, decision to publish, or preparation of the manuscript.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.fishres.2026.107841.

Data Availability

Data will be made available on request.

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