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Review

Quantitative fishery assessment in tropical waters: Stock dynamics and strategy options

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Abstract

This paper explores the possible options for quantitative fishery stock assessment in tropical waters and is composed of four layers *viz.,* concepts, methodologies, data and indicators. The concept promotes the fundamental theory that has been popular in research on stock dynamics, including the possibility of combining it with various doses of intrinsically biological information, from individual fish to regional stocks. After reviewing the concepts, tools and their evolution, an attempt has also been made to propose a few guidelines as the best ways to approach stock assessment and formulate input control or output regulation strategies in the most pragmatic yet scientific manner, thereby ensuring minimal impact on the fishery, fishers and stocks in the medium term.

Introduction

The humanosphere is replete with resources which support, influence and get reciprocated by mankind. Quite a few of the natural resources are unique in the sense that they seem to be self-sustaining yet not inexhaustible. Marine fishery resources are the classic case in this category. In India, marine fisheries are an unavoidable sector that compels the attention of stakeholders and planners alike for special reasons. The marine fisheries sector has been the backbone of sustenance of around a million families settled along the coastline of the country. The moment subsistence level utility is flagged, it demands telescopic attention, which at the finest level would get magnified to a cluster of fleets and the fishers using them. Thus, being a majority tropical climate influenced one, our marine fisheries have all the traits that would be compelling, complicated and confounding to study and understand.

With the sector being much under focus in our country in recent times, quantitative analysis of the trends and the basic stocks that shape them up are real building blocks for policy drafting based on scientific evidence. Hence an utmost rigorous yet robust method of stock assessment that would steward the marine fishery management in our waters can never be under-emphasised. A comprehensive collection of various data types such as biological, experimental, commercial and market data, combined with robust methods for analysing population dynamics within ecosystems, is crucial. This approach helps measure current exploitation levels and develop sustainable strategies, which should be periodically evaluated for effectiveness. This paper aims at bringing the status, possibilities and relevance of various methods and tools prevalent in fishery stock assessment that is best suited for Indian waters at single species as well as simultaneous consideration of multi-species levels with an aim to lead to what can be termed as an ecosystem approach to fishery governance.

This paper is mainly founded on four layers *viz.*, concepts, methods, data and indicators, rounding them off with some introduction to management strategy evaluation (MSE). The concept pitches for the basic idea that has been in vogue in studying stock dynamics ranging from individual fish to regional stocks and also the possibilities of integrating them with different doses of

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intrinsically biological information. A general base is laid on the issue of the applicability of these concepts using methods that are mostly proliferated as software tools. On the data part, certain key issues like the non-availability of experimental cruise data or direct age-based data and adapting length or size-based data to their best possible extents using age-length keys have been discussed. The indicators portion deals with what would otherwise be seen as an inherent part of both method and data. The indices of resource abundance and their simultaneous consideration in the face of multi-gear fisheries, have been introduced in that section. The final section flags the usual process flow that accompanies any scientific evaluation of management strategy, starting from the operational model (OM) to all possible scenario-triggered boundaries as well as vistas.

Concepts

At the conceptual level, fish stock assessment can be categorised as retracing the trajectory of a natural resource which has varying rates of growth and reproduction and an asymptotic upper limit. Be it the tracking of growth in the size of an average fish or the surplus production based overall biomass of a stock, this template fits well for most of the fishery resources. Since quantification is the key in these cases, it becomes inevitable to take the help of formally defined mathematical relationships between various traits of growth, removal or reproduction with the causes. Such relationships are mostly non-linear to start with, given the nature of the perceived trajectories of these phenomena.

It is important to notice that once defined, the cardinal components of assessment like unit stock, equilibrium, steady-state, knife-edge selection and instantaneous growth or mortality get affixed in the backdrop of the procedures that are built on these components and thereby are nearly completely sensitive to them. As these concepts are quite essential for carving out a practically suitable method to analyse the quantitative information about the fishery, their violations need to be taken seriously. Hence summarising the conceptual moorings of fish stock assessment, one can easily say that these are methods which fall in the category of ends justifying the means. This makes the robustness of these methods look impervious and a bit far-fetched. But at the conceptual level, a fishery assessment exercise can have a couple of underpinnings. They might primarily rely on the biology and population dynamics of resources within individual or grouped settings, perceived as part of a continuous biological process. Alternatively, they could involve energy or mass balancing, where functional groups act as key components in the exchange of metabolic forces, forming the basis of trophic layers. Either way, the goal is always to estimate the extent of the extant strength of the resources that define the column of marine area/grid under focus and their future prospects under various plausible scenarios.

Methods of fish stock assessment

Classical methods of fish stock assessment have a couple of generic methodological approaches which are always put in place. They are the estimation of the extent of growth, removal, reproduction and recruitment and resilience. These envisage an entire gamut of fishery starting from the fishing fleet, gear, crew to stock, sub stock and average fish. As it has been mentioned in the concepts section, various known deterministic or stochastic relationships between relevant cause and palpable effect under each of these stages of assessment are put to test and the estimates are arrived at. Various models/methods for stock assessment can be broadly classified into biomass dynamics (surplus production) models, delay-difference models, depletion methods, length-based methods, dynamic size-structured methods, age-structured methods, multispecies/ecosystem models and Bayesian approaches.

In surplus production models (SPM), biomass is modelled as a function that integrates species recruitment, growth and natural mortality while ignoring the age or size structure of the population. The Graham-Schaefer model (Graham, 1935; Schaefer, 1954, 1957; Ricker, 1975; Fletcher, 1978; Gulland, 1983), the Fox (1970) model and the Pella and Tomlinson (1969) model are three traditional models that are frequently used. The biomass declines linearly with increase in fishing mortality in the Schaefer model, which is based on the logistic equation, but exponentially with fishing mortality in the Fox model, which is based on Gompertz growth. More flexibility was provided by the addition of a third parameter by Pella and Tomlinson (1969), but at a cost; the model may be unstable, resulting in estimates with high variances and parameter confounding. There are several modified or extended forms of surplus production models available (Shepherd, 1982; Ludwig and Hilborn, 1983, Freon *et al.*, 1990, Punt, 1994; Restrepo and Legault, 1998; Sathianandan *et al.,* 2021).

By integrating biologically relevant and quantifiable characteristics and taking into account temporal delays in biological processes, delay-difference models expand biomass dynamics models (Hilborn and Walters, 1992). By explicitly modelling age-structured dynamics and the lag between spawning and recruitment, they fundamentally diverge from the aggregate biomass function of biomass dynamics models, but by relying on oversimplified assumptions about growth, survival, fecundity and selectivity, they avoid the complexity of formal age-, size-, or stage-structured models. The fundamental presumptions are that all exploited fish are completely vulnerable to fishing, have the same natural mortality rate and are recruited into the fishery and spawning stock at the same age. Deriso (1980) created the initial model, which was improved further by Schnute (1985, 1987), Kimura *et al.* (1984), Kimura (1985), Fogarty and Murawski (1986) and Fournier and Doonan (1987).

When there is limitation of data, depletion methods provide an effective approach of stock assessment. They look at how measured fish removals (catch) affect the relative abundance of fish that remain, which is quantified by an abundance index, frequently catch rate (catch per unit effort, CPUE), which is typically seen proportionate to population size. Leslie and Davis (1939), DeLury (1947), Moran (1951) and Zippin (1956, 1958) are credited with developing the classical depletion methods. The simplest depletion estimate is splitting the fishing season in half, assuming that the population is closed and that the catch rate is proportionate to abundance during each phase (Seber and Le Cren, 1967).

Length-based cohort analysis (Jones, 1981; 1984) provides estimates of abundance and fishing mortality based on growth parameters, assumptions about natural mortality and a catch length frequency distribution from a population assumed to be in equilibrium. The yield per recruit model (Beverton and Holt, 1957) estimates the number of individuals in each size class over the course of the cohort by starting with an arbitrary number of recruits and projecting them forward depending on fishing and natural mortality. The "per recruit" estimates are then calculated by dividing the total by the total number of recruits. Estimating yield, spawning stock biomass (SSB), or number of eggs by size class is done using weight, proportion of the mature and fecundity by size. These estimates are then added up across all classes.

From the age-structured matrix representation of Leslie (1945) and statistical catch-at-age analyses, dynamic length and stage-structured models were developed (Doubleday, 1976; Fournier and Archibald, 1982; Deriso *et al.*, 1985; Gudmundsson, 1986, 1994; Kimura, 1989). These were made general so that the model might be divided into categories for size, developmental stage, sex, or area (Usher, 1966, 1971; Sainsbury, 1982; Caswell, 1989; Sullivan *et al.*, 1990; Sullivan, 1992). The literature describes many statistical catch-at-age and Virtual Population Analysis (VPA)-based techniques. Numerous pertinent references can be found in Hilborn and Walters (1992) and Quinn and Deriso (1999). A more detailed discussion on the above category of models/methods is available in Sparre *et al.* (1989), Sparre and Venema (1998), Sparre and Venema (1999) and Cadima (2003) and further development on the same can be found in Smith and Addison (2003). Length-Based Spawning Potential Ratio (LBSPR) method was proposed by Hordyk *et al*. (2015a, b), and tested in a MSE framework (Hordyk *et al*., 2015c) and further developed a length-structured version of the LBSPR model that uses growth-type-groups (GTG) to account for size-based selectivity (Hordyk *et al*., 2016).

A lot of research has been done on models that can incorporate interactions among species and more broadly, on interactions from an ecosystem perspective, aside from the categories of the models/methods listed above and the improvements that have been made to them in the last couple of decades. Most multi-species and ecosystem models emphasise on both the lower trophic levels and the biogeochemical components of a system or the target fish species (and potentially their immediate predators and prey). According to Murray and Parslow (1999), Kishi *et al.* (2007) and Gregoire *et al.* (2008), the former typically includes nutrients, phytoplankton and possibly zooplankton or filter feeding groups, while the latter includes one or more species that are targeted by fisheries as well as their immediate prey, predators, or competitors (Magnusson, 1995; Punt and Butterworth, 1995; Hall *et al.*, 2006; Xiao, 2007).

Traditional Lotka-Volterra equations and complex end-to-end models are also used to simulate marine ecosystems. According to the objectives, ecosystem models can be divided into three groups viz., (1) Conceptual models that contribute to a general understanding of ecosystem process, (2) Strategic models that provide information for strategic decision making, and (3) Tactical models that provide short-term management (FAO, 2008). The size-spectrum model, the model of intermediate complexity for ecosystems and Ecopath with Ecosim and Ecospace are a few of the well-known multi-species/ecosystem models.

Size-spectrum model, developed by Andersen and Beyer (2006), is a physiologically-structured process model. The model takes into account two processes involved in the dynamics of fish populations, namely food-dependent growth and size-dependent predation (Hartvig *et al.*, 2011; Persson *et al.*, 2014). The model provides wide use of application in the context of food web dynamics (Hartvig *et al.*, 2011), to evaluate the effects of fishing activity and management strategies (Blanchard *et al.*, 2014), to develop multi-species size spectrum models to the ecosystem of data-poor region (Zhang *et al.*, 2016). This model is more suitable for short-term projections and to make the model more robust and suitable for long-term projections, seasonal dynamics, environmental variability at both spatial as well as temporal scales and economic and social dimensions of fisheries should be addressed in the model.

Model of Intermediate Complexity for Ecosystems (MICE) is intermediate between traditional single-species stock assessments based on the integrated analysis paradigm and whole-of-ecosystem models. MICE attempt to explain the underlying ecological processes for a limited group of populations (<10) subject to fishing and anthropogenic interactions and include at least one explicit representation of an ecological process (*e.g*. interspecific interaction or spatial habitat use). The major components of MICE comprise a model of the ecological system and explain the ecological process of a given population, how it is impacted by anthropogenic factors and how the ecological and human processes are represented in the model. MICE model evaluates the effects of the predator–prey dynamics and impacts of the fishing activity on their biomass (Plaganyi *et al.*, 2014).

Ecopath with Ecosim (EwE) (Christensen and Pauly, 1992; Walters *et al.*, 1997; Walters *et al.*, 1999; Walters *et al.*, 2000; Christensen and Walters, 2004) is an ecosystem modelling software that helps to understand complex marine ecosystems [started at National Oceanic and Atmospheric Administration (NOAA) and developed at the Fisheries Centre of the University of British Columbia (UBC), Canada]. EwE has three main components *viz.,* Ecopath – a static, mass-balanced snapshot of the system; Ecosim – a time dynamic simulation module for policy exploration and Ecospace – a spatial and temporal dynamic module designed for exploring impact and placement of protected areas. With the progress of time, EwE has also incorporated EcoBase, an open access repository of trail blazing models fitted using the software and their metadata.

More examples of these kinds of models include multi-species virtual population analysis (MSVPA) approach (Magnusson, 1995), ERSEM (Baretta *et al.*, 1995), ERSEM II (Baretta-Bekker and Baretta, 1997), OSMOSE (Shin and Cury, 2001a,b; Shin and Cury, 2004), Atlantis (Fulton *et al.*, 2005; Fulton *et al.*, 2007), InVitro (Gray *et al.*, 2006), SEAPODYM (Lehodey *et al.*, 2003), APECOSM (Maury *et al.*, 2007), NEMURO model (Kishi *et al.*, 2007), LeMans (Length-based Multispecies analysis by numerical simulation) (Hall *et al.*, 2006), SSEM (Sekine *et al.*, 1991), CAEDYM (Reichert and Mieleitner, 2008), TEM (Raich *et al.*, 1991) as well as CEM and SEM (Cluer and Thorne, 2014). A detailed discussion of these models is given in Fulton (2010).

Another category of stock assessment methods is those which use Bayesian methods. Since classical methods tend to rely on deterministic principles, with occasional use of frequentist stochastic estimations, such as separating normally distributed cohorts from mixed population samples based on length frequencies, criticism has emerged regarding these approaches. This criticism has opened up numerous possibilities for exploring stochastic non-frequentist analysis methods.

Although frequentist approaches do not provide a coherent method for incorporating prior knowledge, they do provide non-parametric techniques, which allow for the relaxation of the assumptions surrounding error distributions. In Bayesian approaches, parameters are thought to have a (posterior) probability distribution that depends on the prior probability distribution and the likelihood of the parameter given the data. Prior probability distributions provide a formal method for incorporating knowledge from additional sources and are formally distinguished from data, but specifying prior distributions is not straightforward and results may be sensitive to the assumed prior distributions. Additionally, the methods require a significant amount of computation.

Bayesian methods alongside Monte Carlo simulation and bootstrapping were applied on each of the stages of modelling, thereby expanding the scope of inferential possibilities and more robust estimation of standard errors of parameters estimated. Hence with the evolution of computational power and the advent of more powerful multi-parameter optimisation routines like Automatic Differentiation Model Builder (ADMB) and Template Model Builder (TMB), all these traditionally opted methods were subjected to new kinds of analyses. This helped to enhance the possibilities of universally optimum solutions for the key parametric nonlinear formulations. There are also cases involving other interesting optimisation concepts like Simulated Annealing and Genetic Algorithm (TropFishR).

The Bayesian approach to stock assessment calculates the likelihoods of various hypotheses based on data for the stock in question and conclusions drawn from data for other stocks or species. These probabilities are necessary if the outcomes of various management activities are to be assessed using decision analysis. It is possible to admit the whole range of uncertainty and leverage the collective historical experience of fisheries science when using the Bayesian method to stock assessment and decision analysis to estimate the effects of proposed management actions (Punt and Hilborn, 1997). Recently, Bayesian approach has been rigorously implemented in developing stock assessment strategies [ParFish (Medley, 2006; Wakeford *et al.*, 2009), CMSY (Palomares and Froese, 2017; Helias, 2019), CMSY++ (Froese *et al.*, 2021), AMSY (Froese *et al.*, 2020), LBB (Froese *et al.*, 2018), JABBA (Winker *et al.*, 2018), BayesGrowth (Smart, 2020)] as it provides reasonable estimates even for fairly complex stock assessment models.

Although the methods mentioned above are commonly used by numerous research and governance bodies of various countries to assess their marine fish stocks, their effectiveness relies heavily on estimating the abundance or biomass of both exploited and unexploited fish stocks. Nevertheless, the reliability and effectiveness of these stock assessment techniques are always subject to debate, particularly regarding their uniform application across diverse types of fisheries practiced worldwide. The use of homogenous indicative metrics gives a fair representation of the stock status of all countries and can be compared amongst them over a temporal interregnum. One such set of indicators is Stock Status Plot (SSP). Pauly *et al.* (2008) created (and coined the name) 'Stock Status Plot' for a UNEP compendium on Large Marine Ecosystems. Stock status plots are bivariate graphs summarising the status (*e.g.,* developing, fully exploited, overexploited) through time, of the multispecies fisheries of a fished area or ecosystem (Pauly *et al*., 2008; Kleisner and Pauly, 2011; Kleisner *et al.*, 2013; Varghese and Jayasankar, 2023; Varghese *et al*., 2023). A summary of some of the methods discussed above along with the data requirements, major outputs and reference for details and model assumptions are given in Table 1.

Pros and cons of the methods

Any assessment model must rely on simplified representations of the real system and make fewer assumptions. For both basic and complex models, there should be a trade-off between the number of parameters to be estimated and the model assumptions. Comparative studies have shown that less complex strategies can sometimes outperform more sophisticated ones (Richards and Schnute, 1998). Because they are typically more visible than sophisticated methods and are more likely to yield solid results, simple models that maintain biological realism should not be overlooked. Even though several multi-species/ecosystem model frameworks are available in the literature, it requires more effort to translate the model output for tropical fisheries management. Most of the multi-species/ecosystem models are more suitable for closed ecosystems where interactions can be easily modelled. Besides, multi-species/ecosystem models have several limitations due to their size and complexity, as the data needs can be challenging to meet in the majority of the scenarios.

The significance of including dynamic environmental drivers in the framework for stock assessment modelling should also be underlined, as most conventional models do not explicitly account for the impact of environmental trends or stochasticity. There is still a knowledge gap when it comes to maximising the effectiveness and accuracy of the current stock assessment methods as well as evaluating the synergistic effects of climate change on stock status. The main challenge, however, is gathering spatial-level information at the required resolution. The way forward could be to attain a gridded estimate of abundance through passive geo-referencing coupled with predictive modelling along with a participatory validation of the same with the involvement of fishermen from various marine fishing sectors.

The Bayesian approach could be useful in reducing the uncertainty associated with the choice of model parameters. Instead of taking point estimates for the parameters in the model equation, interval estimates may give a wider search space for getting a better fit. However, care must be taken when choosing prior distributions to prevent drawing erroneous conclusions. Punt and Hilborn (1997), advised to use Bayesian approaches for decision analysis in fisheries, but they also highlighted the necessity to use a variety of alternative methodologies, emphasising outcomes that are resistant to model selection will be given greater weight.

Summing up for the Indian waters, which often witness the conundrum triggered by huge quantity of data extremely focussed on one facet of information aquifers of fish stock assessment, the landings and size sample datasets collected by research institutions like ICAR-Central Marine Fisheries Research Institute (ICAR-CMFRI) from commercial vessels. Such an information is quite vital and quantitatively sufficient for deputing most of the methods discussed above and the publications and research reports documented in the past two and a half decades are a case strong enough to buttress this (eprints@cmfri; http://eprints.cmfri.org.in). But the intertwining of common factors that support

Table 1. List of selected methods along with data requirements, major outputs and key references*

Methods/Models	Input data requirements	Major model outputs	Key references for details and model assumptions
Stock Status Plots	Time-series of catch	Status of the stocks over years	Pauly *et al.* (2008); Kleisner and Pauly (2011); Kleisner *et al.* (2013); Pauly *et al.* (2008); Varghese and Jayasankar (2023); Varghese *et al*. (2023)
Biomass dynamics models / Surplus production models	Time-series of catch and Index of abundance	Estimates of carrying capacity (K); Population growth rate (r); Maximum Sustainable Yield (MSY); Predicted biomass (B); Biomass at MSY (B_{MSY}); Fishing mortality (F); Fishing mortality at MSY (F_{MSY})	Graham (1935); Schaefer (1954, 1957); Ricker (1975); Fletcher (1978); Gulland (1983), Fox (1970); Pella and Tomlinson (1969); Shepherd (1982); Ludwig and Hilborn (1983), Freon *et al*. (1990), Punt (1994); Restrepo and Legault (1998); Sathianandan *et al*. (2021)
CMSY	Time-series of catch and species resilience	Estimates of carrying capacity (k); r; MSY; Relative biomass (B/k); B_{MSY}; F; F_{MSY}; F/ F_{MSY}; B/ B_{MSY}	Froese *et al*. (2018); Palomares and Froese (2017); Froese *et al*. (2021); Varghese *et al*. (2020); Suresh *et al*. (2021)
BSM	Time-series of catch and Index of abundance	k; r; Catchability (q); MSY; B/k; Biomass B_{MSY}; F; F_{MSY}; F/F_{MSY}; B/B_{MSY}	Froese *et al*. (2018); Palomares and Froese (2017); Froese *et al*. (2021); Varghese *et al*. (2020); Suresh *et al*. (2021)
AMSY	A time series of CPUE (or index of biomass), prior ranges for r and relative stock size (Bt/k)	Maximum sustainable value (MSYq) of relative catch Cq; relative carrying capacity (kq), or the CPUE, if there were no fishing; F/ F_{MSY}; B/ B_{MSY}	Froese *et al*. (2020)
LBSPR	Case1: Asymptotic length (L_{∞}); instantaneous growth rate (K); M/K ratio (natural mortality divided by von Bertalanffy K coefficient); Length at 50% maturity (L_{mat50}); Length at 95% maturity (L_{mat9}5); Length at 50% selectivity (SL_{50}); Length at 95% selectivity (SL_{95}); F/M ratio or SPR; Bin Width; Bin Maximum; Bin Minimum	Case1: Simulated length composition based on the inputs provided	Hordyk *et al*. (2015a, b and c); Hordyk *et al*. (2016); Suresh *et al*. (2021)
	Case2: Length-frequency data; M/K ratio; L_{mat50}; L_{mat95}	Case2: Estimated Spawning Potential Ratio (SPR)	
LBB	Length-frequency data over years; L_{∞}; L_c (Length where 50% of the individuals are retained by the gear-Length at first capture) and L_{mat50}, if available	Z/K; M/K; F/K; L_c; L_{c_opt} (Optimum Length at First Capture); L_{mean}; L_{opt}; F/M; B/B_0	Froese *et al*. (2018)
JABBA	Time-series of catch, CPUE (or Index of abundance) and standard error of CPUE (if available); priors for r, K and B/K	Estimates of carrying capacity (K); r; MSY; predicted biomass (B); B_{MSY}; F; F_{MSY}, Projection of the reference points under defined scenarios	Winker *et al*. (2018)
sraplus	Case 1: “Catch-only” SIR model Time-series of catch	Case 1: Catch/ Maximum Sustainable Yield (MSY); Biomass at MSY (B_{MSY}); Fishing mortality (F); Fishing mortality at MSY (F_{MSY}); F/ F_{MSY}; B/ B_{MSY}; Rate of depletion	Ovando *et al*. (2021)
	Case 2: Time-series of catch, Fisheries Management Index (fmi) and Swept Area Ratio (sar)	Case 2: Catch/ Maximum Sustainable Yield (MSY); Biomass at MSY (B_{MSY}); Fishing mortality (F); Fishing mortality at MSY (F_{MSY}); F/ F_{MSY}; B/ B_{MSY}; Rate of depletion	

*Only selected few methods/tools/models available for fish stock assessment are listed resources of similar ilk and the fact that they have high probability to be netted by diverse modes of fishing, keeps the evolutionary quotient of researchable components of our waters unique.

Challenges in tropical waters

Assessing fish stocks in tropical waters presents several unique challenges due to the complexity and diversity of tropical marine ecosystems. Tropical waters are often characterised by high species diversity, with a wide variety of fish species inhabiting coral reefs, mangroves, seagrass beds and other coastal habitats. Assessing the abundance, distribution and population dynamics of numerous species that too simultaneously and when they have niche interdependence can be challenging, particularly when data is limited. Such a dispensation makes the very conceptualisation of the tropical ecosystem a very evolutionary and intertwined agglomeration of sub-systems. Assessing fish stocks requires understanding the habitat preferences and movement patterns of target species, which can vary spatially and temporally. Data on fish populations in tropical waters are often limited, fragmented, or incomplete especially when data-intensive models are to be attempted.

Data

The data that defines any kind of assessment has to be qualified on two counts *viz*., precision and continuity. Even if it is a cross-section data, a sort of range continuity is to be ensured for better inference. But stock assessment data traditionally fall under the category of time series, and hence both these integrities are equally pronounced and must be adhered to. Starting from relative appraisals to trend analyses to much more in-depth computations, data on marine resource dynamics can be both alluring and challenging at the same time. With the information on fisheries spreading from sea to land, biomass to landings, there could be more than one criterion to define data as sufficient or otherwise. The usual data-poor situations are usually defined both on qualitative as well as quantitative norms. Starting from experimental cruise-based data to secondary data on exports and processed fish, anything and everything can constitute data as on date.

While data richness can always be contested, the concepts and methods have been quite open and accommodative when it comes to dealing with limited to moderate datasets. For multi-gear-fleet multi-species fisheries, the minimum data requirement is the catch and effort time series. The species-wise area-wise (sub stock) catch or landings and the corresponding nominal efforts of gear-fleets may be the least one can look forward to when it comes to assessing such a fishery. Though catch-only methods are quite popular as data-limited fishery assessment options, for a mixed resource fishery using multiple gears, not all selective, the ideally suited data could be a time series of five years and above of these catch and effort. The nominal efforts need to be processed for their differential catchability, which forms one major sub-domain called effort standardisation. In literature, methods varying from proportion-based comparison alongside a standard gear to Nelder-Mead algorithm-based optimisation of the various nominal catch rates against gears are available. Also proposed are methods like adopting a general linear model-based approach alongside utilising uniquely relevant distributions like Tweedie distribution. In Indian waters, the most suitable approach would involve combining the nominal values of the fishing gears and organising them into categories based on a summarised hierarchy including month, year, and region. Developing methods that would entail integrating these categories into the primary model used for estimating reference points such as Maximum Sustainable Yield (MSY) will be the best choice. The best example is the one adopted in the Pella-Tomlinson kind surplus production function fitted for estimating optimum fleet size (Sathianandan *et al.,* 2021). However, simple and easy-to-use methods based on the measures of central tendency and dispersion of the data are recommended for resources which are caught by a limited number of gear types (Varghese *et al.,* 2020).

As regards sampling design to be adopted for both landings as well as biological sampling, the stratified random sampling at various stages that has been standardised and evolved over the years at ICAR-CMFRI is strictly adhered to (Alagaraja, 1984). Based on decades of studies conducted by researchers in Indian waters and the evolutionary patterns of fishing methods and fleet dynamics, sufficient caution must be taken while sampling for biological traits to ensure them to be as much diversified as possible with respect to gears. There has been a plaguing issue of gear selectivity and the sample's representativeness which adds to the agony of the researcher. However, this can be well addressed by following the following scheme:

- At least five months of sampling in succession, with each month having two decently spread gaps within the month.
- Ensuring at least minimal samples from all possible gears that land the resource
- In case of obvious selectivity biases of the respective samples but covering different size groups, weighted admixture of the counts would be the way forward. The preferential sampling that is intrinsic to commercial landings-based surveys often lead to more focus on the biomass of targeted resources and their favourite spatial niches, which would create an over-estimation bias in the normal run. With the gear selectivity too getting added, such samples may tend to boost or underplay the size and thus the age groups, which would be a challenge to estimate the parameters leading to reference points.
- In case the available data is skewed to one particular phase of size and growth of the animal, suitable augmentation of the data with simulated tails using multinomial distribution or selecting models that have suitable amended prior parameterisation in case of utilising Bayesian methods is advised.

When the catches, both intentional and unintentional, follow a correlated pattern and the units pressed to harvest them too have differential selectivity leading to multiple catchability, such a set of possible steps must be adhered to while performing exploratory analysis. In case of severe bias due to the preferential selective sampling, suitable methods like model-based sampling with zero inflated observational distribution would be a very good option to put to practice.

Indicators

The main hurdle or moot question in any stock assessment exercise in a typically data-constrained environment is the selection of indicators of biomass abundance. The biomass, either expressed as weight or in numbers, is the real component of the latent part in most of the commonly used methods like delay difference models or state space models. The biomass being in the realms of components to be estimated themselves pose a distinctive challenge when it comes to estimating the interim function that leads to the computation of biological or economic reference points. Hence proper selection of the indicator for the same is very much essential. Though it is always a practice to use catch rate, either as catch per unit effort or catch per unit fishing hour or catch per unit of HP effort or per unit of fuel utilised, would always be popping in one's mind, it is to be handled very carefully. Occurrence of frequent zeros in catch rates, especially when the same resource is landed by multiple gears must be approached with a lot of deftness. One such option is provided by zero-inflated model fitting, involving distributions like Tweedie or Poisson. However, it is always advisable that wherever possible, landings independent estimation of biomass by utilising methods like VPA or stock recruitment relationships (SRR) may be attempted for the various size groups and the same may be combined towards the end to arrive at an independent estimate of SSB. The indicators may also vary from the most commonly targeted production or value. For instance, MSY equivalents as derived from yield per recruit model and Spawning Potential Ratio and other relevant measures of abundance will be of more comprehensive relevance.

Another interesting development in expanding the concept of MSY from single species to multi-species is the multivariate MSY, which relies on aggregating data from multiple fleets capturing various species simultaneously. One of the most prominent methods of such computation is based on Nash Equilibrium, wherein the stage at which any given species does not get influenced after attaining an optimum, irrespective of the variation in the capture of competing and cohabiting resources (Thorpe, 2019). Such approaches coupled with full extraction and utilisation of prior knowledge of the species being studied would always come in handy while assessing stocks of our subcontinent.

Strategy options

The immediate state of transition for these indicators of stock health are the management strategies. Depending upon the quantum and direction of the reference points, strategies for either input control such as regulation of size, number and kind of fishing gears or output control measures, like precautionary levels of fishing and limitations on the size of fish caught during specific seasons are spelt out. Such strategies can always be evaluated computationally by following a sequential set of analytical and simulation maneuvers.

A typical effort to evaluate management strategy would involve collating a set of relevant sets of growth, reproduction and ecosystem level scenarios of fishery resources of the zone under focus and their most probable fishing fleet generically categorised based on the gears, bound by mathematical or statistical relationships, known as operating models (OM). These OMs are then constrained and conditioned to match the various real life scenarios like admissible range of CPUEs, which would make the OMs more realistic to the zone under study. Uncertainty is added as stochastic error generated as part of what is called as observation error, thereby preparing the simulated dataset to next level. Thus, the simulation process that is taken care of at the OM level gets transformed into a stage wherein the resultant data gets amenable to stock assessment of any predetermined kind to arrive at the reference points as the derived input or output control rules. Then follows the most curious stage of the exercise wherein the outputs of the assessment-based maneuvers are subjected to possible implementation errors like overages and the results are referred into the OMs and the cycle gets repeated. Based on these closed looping trials, the best management strategy as reflected in input and output control mechanisms is zeroed in and finalised. As these are computationally intensive, such combination of simulation and looping are executed by routines custom made for such purposes, MSEtool (Carruthers and Hordyk , 2018) being an example.

Conclusions

Upon reviewing the concepts, tools and their evolution, the following possibilities emerge as the best rules to tackle the stock assessment and formulation of strategies that nudge input control or output regulation in the most practical yet scientific way, thereby ensuring minimum impact to the fishery, fisher and stock in the medium run.

- For a catch only (zone/area-wise) series intuitive analysis, Catch Maximum Sustainable Yield Model (CMSY) or Generalised Additive Model (GAM) can be the approach adopted to have a spatio-temporal analysis.
- Frequentist or Bayesian approaches (CEDA, TropFishR, BSM, JABBA and many more) which are based on Surplus Production and Stock Reduction models, can be used when both catch and effort (standardised) series are available.
- For size-based samples (raised to catch and effort levels), YPR, LBB, LBSPR and LeMaRns, which rely upon modelling intrinsic or latent dynamics or prediction models, may be used.
- Stock Synthesis and similar models, characterised by their comprehensive approach to modeling while maintaining a high level of data granularity, are well-suited for age-based analysis incorporating length-age key and/or live cruise/experimental cruise data. These models also offer the advantage of incorporating external and abiotic factors such as climate and oceanographic variables into their formulation.

A review and objective appraisal of the information present in our marine fisheries, along with the assessments derived from it, clearly indicates a strong foundation in terms of conceptual understanding. However, from a methodological standpoint, there is need for a comprehensive approach that encapsulates the most appropriate methods for our fisheries, with a primary focus on sustaining the livelihoods of fishers at its core.

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