Fisheries Oceanography

An Integrative Approach to Fisheries Ecology and Management

Edited by

Paul J. Harrison

and

Timothy R. Parsons

*Department of Earth and Ocean Sciences,
University of British Columbia, Canada*

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Commentary:
Can We See the Future?

K. Denman

Introduction

Increasingly, we as scientists are being asked by society to forecast the future. This expectation is especially strong in fisheries science. Yet, as fisheries scientists, we have been trained to observe natural systems in order to increase our understanding of how those systems behave rather than to forecast their future behaviour. Modelling is perhaps the most powerful tool available to analyse observations of natural systems to increase our understanding of their 'system behaviour'. The excellent chapter in this volume by Dr Ware capably describes the state-of-the art of modelling and analysis of marine ecosystems, and future directions in this area. However, models for improving our understanding of complex systems are not necessarily the best models for forecasting the future behaviour of these systems. In the same manner that atmospheric scientists study how the atmosphere works, while meteorologists endeavour to forecast the weather (and climate), we might expect a divergence in fisheries science between modelling activities aimed at increasing our understanding and modelling activities aimed at forecasting the future. Ideally, there should be close and frequent interactions between the two activities, but they will be different. For example, the assimilation of data is essential to initialize and to maintain forecast models as near as possible to an evolving continuously-observed system, but data assimilation, while currently a high profile activity, is not necessary in models designed to increase our understanding of a complex system. In this note I shall broaden the topics covered by Dr Ware in his chapter, by reviewing the development of multidisciplinary ocean models in the context of building up a capability to forecast the future state(s) of marine ecosystems.

Steps to forecasting

Without becoming involved in the mathematics and philosophy of prediction, one can describe several stages that we, as individuals and as a community of scientists, pass through in developing a capability to forecast the future behaviour of various systems. To continue to improve our ability to forecast, it is necessary regularly to evaluate our present capability and to pass on that evaluation to those using our forecasts. With reference to Table 7.3, I shall describe the sequence of stages. The

Table 7.3   Steps to forecasting

1. Wild guesses
2. Back-of-the-envelope calculations
3. Static 'spreadsheet' or 'flowchart' analyses
4. Predictive regression equations
5. Dynamic models of future behaviour (increasingly comprehensive):
   – *scenarios*
   – *projections*
   – *predictions*
6. Analysis of risk

first attempt to provide a forecast is the 'wild guess'. It is not quantitative and is not usually considered to be based on scientific knowledge. For example, a wild guess might be the statement that 'if the ice cover in the Arctic Ocean melts, then sea level will rise'. However, after a bit of scientific thought, we will conclude that since most of the ice covering the Arctic Ocean is floating, it already displaces a volume of sea water equal to its own mass, and its melting will have negligible effect on sea level. What if the ice caps sitting on Antarctic and Greenland were to melt? Initial 'Back-of-the-envelope calculations' a few decades ago led to sensational headlines that sea level would rise 60–100 m. However, 'static spreadsheet or flowchart analyses' and most recently 'dynamic models' indicate that global sea level is likely to rise less than a metre in the next century (e.g. Warrick *et al.*, 1996), with a range of uncertainty slightly larger than the mean prediction. The application of scientific knowledge has transformed what appeared to be a major catastrophy in the future into a change that can in principle be managed.

'Static spreadsheet or flowchart analyses' do not vary in time, and include steady-state models described by Dr Ware, who presented the ECOPATH models as examples. Meteorologists refer to such models as 'diagnostic models'. In a marine ecological context these analyses are referred to as flow analysis (e.g. Fasham, 1984) or inverse analysis (e.g. Vézina and Platt, 1988). Generally, these methods provide a starting point for dynamic models (as referred to by Dr Ware), by taking all known information about an ecosystem, pool sizes, flows, etc., and trying to estimate a consistent matrix of all the compartment pool sizes and the flows between the compartments. This complementary nature of the two approaches, static analyses and dynamics models, is illustrated by two recent studies of the planktonic foodweb at Ocean Station P in the subarctic NE Pacific. Vézina and Savenkoff (1999) performed an inverse analysis of all the pool sizes and fluxes measured on three cruises in three different seasons. For each season they inferred consistent fluxes in a rather complex version of the foodweb. Denman and Peña (1999) simulated the annual cycle at OSP with a one-dimensional coupled mixed layer–dynamic ecosystem model. Their system was simpler (four ecological compartments), but they could simulate rapid temporal change (15 minute timestep) and fine vertical (2 m) structures.

Spreadsheet or flowchart analyses often lead to predictive equations for the behaviour of a system based on statistical regression techniques. Regression equations can provide useful information to manage an ecosystem or fisheries for a time, but they are likely to fail eventually for two fundamental reasons. First, the observations used in developing the regression equation(s) are drawn from a parent population. According to the Central Limit Theorem, the subset of observations of a mean drawn from a parent population will be normally distributed even if the parent population is not. However, even if the parent population is normally distributed, subsampling is rarely adequate to estimate properly the likelihood of rare extreme events, which are usually what we most want to be able to predict. Second, in a changing climate, the parent population or distribution may itself be shifting such that the regression equation used for predictions was developed from subsampling of a parent distribution significantly different from that now in existence. In other words, the system now regularly occupies states outside of the range of states from which the regression equations were developed.

Environmental science, including fisheries oceanography, is progressing such that the only acceptable mode of forecasting will be the final one in Table 7.3: dynamic models of future behaviour. With continuously improving computer access, modelling experience and large integrated multidisciplinary field studies, we expect to be moving towards increasingly comprehensive coupled physical/ecological models. The first stage of dynamic modelling will provide 'scenarios', probably without predictive value. Scenarios are of value for managing ecosystems because they can show us in graphic terms how changed ecosystems might appear and how they might function. In other words, they can train our intuition and imagination. These models should then evolve towards models that provide 'projections' – simulations of future ecosystem state and behaviour that we have confidence could happen, given the initial conditions and parameter values used in the model. The next stage is an empirical sensitivity analysis or Monte Carlo modelling whereby the initial conditions and the parameter values (and possibly the functional forms) are varied over the range of likely values. The resulting 'forecast' or 'prediction' is not a single most likely future state, but a range of 'projections', where enough simulations have been conducted so that different probabilities can be assigned to different subranges of projections.

There are philosophical arguments that models, because they are only analogues of the real world, cannot be validated but only evaluated with observations (Oreskes *et al.*, 1994). However, I note that it is almost axiomatic to state that confidence in forecasts will increase with the increased use of observations in the forecast models, whether through improved initial conditions and boundary conditions, improved parameter formulation and estimation, and/or data assimilation.

State-of-the-art

In addition to the progress in ecosystem modelling as described by Dr Ware, Getz (1998), in a readable yet comprehensive account, reviews the progress and suggests future directions in the '... art of modeling in population ecology'. Like Dr Ware, he argues for simple or 'top-down' approaches rather than 'bottom-up' approaches to models of population ecology. In the 'bottom-up' approach (starting with all the building block submodels of individual processes), he warns pragmatically that 'The finer the level of resolution at which the modeler begins ... the greater the opportunity unwittingly to leave out important bits and pieces that contribute critically to the higher-level processes of interest'. Another disadvantage of the bottom-up approach follows from considering a compartment model, where each compartment exchanges matter or energy with each of the others. As the number of compartments N increases, the number of one-way flows increases as $\frac{1}{2} N(N-1)$, i.e. approximately as N^2. Each flow formulation requires at least one parameter. But in practice, the uptake of nitrate by phytoplankton, for example, is usually formulated to depend on at least 4 parameters describing non-linear dependencies on both light and nitrate. A typical planktonic ecosystem model with 6 or 7 compartments will require the estimation of perhaps 50 parameters based on observations. Rarely can all the parameter values be estimated from observations.

The development of increasingly comprehensive coupled models for forecasting requires the use of up-to-date ecological and ocean circulation models. Especially along the continental margins, where most fisheries take place, physical circulation and mixing profoundly affect the behaviour of fisheries food webs. Thus, inclusion of physical influences in models of regional marine ecosystems are essential to forecasting their spatial and temporal behaviour, as emphasized by Dr Ware in his chapter. The natural question arises: how much physics is enough?

Generally, larger marine organisms have greater capability for directed motion than do smaller organisms. At what level must this behaviour be included explicitly in models: when the directed motion is significant relative to the advective motions of the currents and mixing represented in the physical model. We can organize these ideas with reference to Fig. 7.22, reprinted from Denman (1994), which compares time and space scales of motions characteristic of the upper ocean with those for phytoplankton, zooplankton and fish. The 'directed motility' scales (diamonds) for phytoplankton and zooplankton overlay scales of typical motions in the upper ocean, suggesting strong interactions with the flow field. Fish can swim for short periods considerably faster than any currents, suggesting that physical motions would usually be a small correction on the swimming behaviour of larger fish in a coupled model.

The so-called 'ecological scales' (connected circles) all lie along the rotational range (oceanic mesoscale eddies) suggesting that these distances covered by
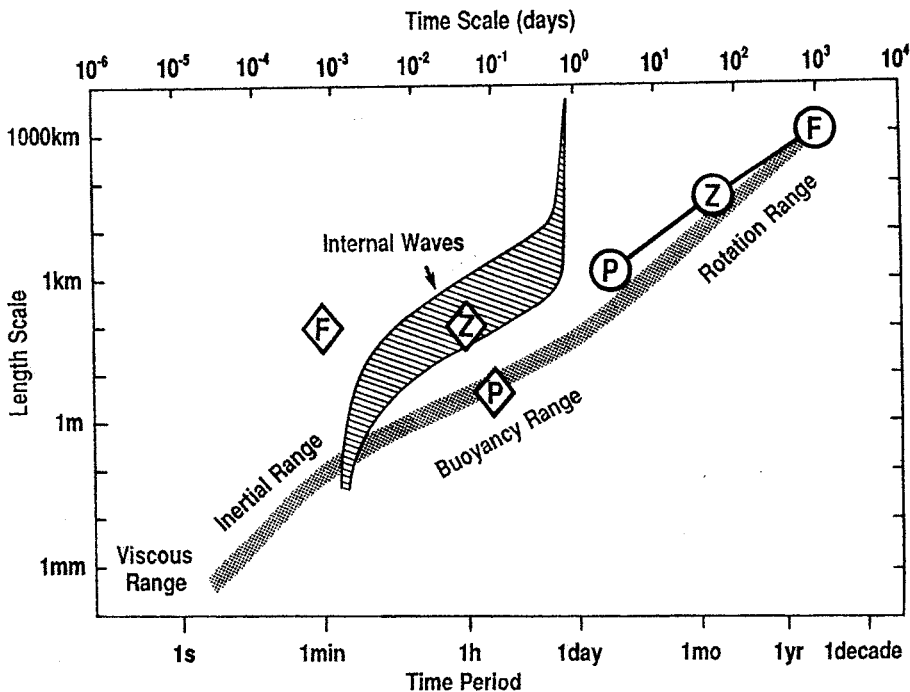
Fig. 7.22   Space-time continuum for resonant motions in the upper ocean. From right to left, the shaded band traces out preferred scales for large mostly two-dimensional eddies in the ocean (Rotation Range), through scales less than or equal to the thickness of the upper mixed layer, which are becoming three-dimensional but are flattened by stratification and gravity (Buoyancy Range), through to three-dimensional small scale 'turbulent' motions (Inertial Range), ending in the viscous range where motion is converted by friction into heat. Internal waves occupy the striped area. The connected circles labelled 'P', 'Z' and 'F' represent 'ecological' scales for phytoplankton, zooplankton and fish; the similarly labelled diamonds represent 'directed motility' scales. (From Denman, 1994.)

phytoplankton, zooplankton and fish are controlled by currents. We might also define a 'migration scale' for fish. Northern cod in the N. Atlantic and salmon in the subarctic NE Pacific Ocean can swim at least $30 \, \text{cm} \, \text{s}^{-1}$, which averaged over a season, say 100 days, gives a migration distance of order 3000 km. This scale (in time and space) would be located near the exponent '2' in '10^2' on the label of the upper axis of the figure. What is the comparable distance for ocean currents in 100 days? Shelf-edge currents off western N. America can easily average $20–50 \, \text{cm} \, \text{s}^{-1}$, suggesting distances of 2000–5000 km in 100 days. Mean currents over the top 100 m in the subarctic Alaskan gyre average $5–10 \, \text{cm} \, \text{s}^{-1}$ (e.g. Thomson *et al.*, 1990) suggesting distances of 500–1000 km over 100 days. That such currents can affect the migration routes and timing of returning salmon has been convincingly illustrated through the use of a simple Ocean Surface CURrent Simulations model (OSCURS) by Thomson *et al.* (1992, 1994) and Ingraham *et al.* (1998).

In parallel with the advances in models of population ecology have been advances in modelling ocean currents. McWilliams (1996) has recently reviewed progress in modelling the large-scale ocean general circulation, but perhaps more relevant in our context is the state of coastal ocean modelling. Because of the diversity of approaches to modelling coastal circulation, there are a number of highly developed models in two main categories. The first is the finite element approach where the model grid consists of many connected triangles of differing sizes and shapes representing coastline and bottom bathymetry with resolution that varies spatially according to assumed scales of motion and/or the resolution required. The second is the layered approach where the horizontal grid is more or less rectangular (often oriented with major axes alongshore and across the shelf), but the vertical resolution varies with bottom depth: a constant number of layers are compressed or expanded vertically in proportion to the local bottom depth. These two approaches are being used in two high energy continental margin regions coupled to food web models that include Lagrangian or Individual-Based Models (IBM) where individuals or cohorts of fish are followed as they are moved around by the currents, and in some models as they feed on the modelled zooplankton prey fields.

The first is a finite element model that has been developed for the Gulf of Maine and Georges Bank off the eastern seaboard of North America (Lynch *et al.*, 1996). It has been used to study the dispersion, retention, and settling of cod, haddock and scallop larvae around Georges Bank for different life histories (Werner *et al.*, 1993; Tremblay *et al.*, 1994), and recently to study the transport, population dynamics and life history of the copepod *Calanus finmarchicus* in the same area (Lynch *et al.*, 1998; Miller *et al.*, 1998).

The second is a layered ocean circulation model of the circulation in the vicinity of Shelikof Island, in the northwestern corner of the Gulf of Alaska (Hermann and Stabeno, 1996). Embedded in this model is a Nitrate-Phytoplankton-Zooplankton (NPZ) model (with 14 stages/species) with a horizontal spacing about 5 times coarser than the physical model. This model provides food or prey for walleye pollock in a spatially explicit IBM model (Hinckley *et al.*, 1996). In Hermann *et al.* (1996, 1999) the combined comprehensive model simulates the movement and survival of pollock for different years with different wind histories. As in the Gulf of Maine, at least a decade of field studies and model development has led to the present coupled model. Hermann *et al.* (1999) include a table describing the time on a CRAY YMP for a season's simulation: 125 h for 270 days of the circulation model, 5 h for 95 days of the prey (NPZ) model, and 5 h for 210 days of the pollock IBM model. Over 90% of the computer resources have been dedicated to the circulation model. We have the experience and observational base required to evaluate simulations of the circulation and to state with confidence that we need such high resolution in the circulation model. We might expect in the next decade also to develop a similar confidence in the necessary and justified level of detail in the foodweb and IBM model components, based on modelling and observations being carried out in cooperative programmes like GLOBEC.

Conclusions

It is from these types of models that we are likely to develop comprehensive forecast models in fisheries oceanography. However, the final step to forecasting in Table 7.3, 'risk analysis', may not yet be considered as part of fisheries oceanography, but it should be part of forecasting methodology if the forecasts are to be fully exploited in resource management[1]. In risk analysis, the range of predictions is divided up into different subranges with different probabilities. A level of risk, or seriousness of consequence, is then assigned to each of these subranges. From a management perspective, low risk, low probability subranges should be ignored, and high risk, high probability subranges should be examined first. Are we confident that these particular simulations represent the most probable outcomes and that the risk is highest? If not what new knowledge is required to improve our forecasts? If we are confident of our forecasting of both probability of outcome and assigned risk, then can we develop procedures to avoid the outcome? If not can we design and implement mitigation or adaptation measures to deal with the likely outcomes? Sometimes there are no high probability, high risk subranges in the forecast, but there are low probability, extremely high risk subranges. In such cases, then management efforts should be directed towards avoiding those outcomes.

Risk analysis and providing forecasts would usually be considered to be the responsibility of resource managers rather than of fisheries scientists. However, the process must be iterative: assessment of the scientific underpinnings of the forecast methodology in light of new scientific knowledge should be ongoing, and new scientific research should be conducted to address gaps identified in our scientific understanding with the aim of improving the forecasting methodology.

The combined impacts of human activities and climate change threaten many fisheries ecosystems, lending urgency to our quest to improve our ability to see the future. Let us hope that Dr Ware will write a sequel to his chapter, in a few years' time, where he can again report that progress had been significant in the previous decade, not only in our understanding of how marine ecosystems function but also in our abilities to forecast their future behaviour.

Note

(1) Here we use 'risk-analysis' in the decision theory sense, rather as 'the probability of something undesirable happening', its usual meaning in the fisheries literature. See Francis and Shotton (1997) for an explanation of the distinction.

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