A perspective on the use of spatialized indicators for ecosystem-based fishery management through spatial zoning

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Although much work has been done developing system-level indicators for ecosystem-based fishery management (EBFM), few of those proposed include a spatial component. Even in single-species management, time and area closures have been applied without a clear understanding of what their effect might be on identifying overfishing thresholds and other reference points. For EBFM, spatial zoning of the marine environment, including no-take marine reserves and areas where destructive fishing gears are prohibited, may become a prime management tool. Therefore, indicators of the effectiveness of spatial management will be required, along with an understanding of how indicators related to other objectives will be influenced. We review single-species models that have been used to model spatial zoning, including potential bias in assessment and current work on effort reallocation after area closure, as well as available ecosystem-based models and metrics and how they might account for spatial management. Metrics that can be derived from explicitly spatial approaches such as GIS-based ecosystem and fishery evaluations are also discussed.

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Introduction

Greater consideration of ecosystem processes in fisheries management has been widely recognized as desirable, both to ensure the sustainability of fisheries and to maintain the non-fisheries benefits of marine ecosystems to society (EPAP, 1999; FAO, 2003; Pikitch et al., 2004). The objectives of ecosystem-based fisheries management (EBFM) include sustaining ecosystems as well as fishing yield (Babcock and Pikitch, 2004), and achieving the objectives requires the use of indicators (a measurable quantity for evaluating objectives), reference points (benchmark values), and performance measures (Sainsbury and Sumaila, 2003).

Ecosystems are spatially heterogeneous, and spatial patterns and processes are important to ecosystem structure and function, whereas the distribution of fishing activities depends on the distribution of the targeted resource (which in turn depends on oceanographic habitat and interspecific interactions), as well as economic considerations (Pelletier et al., 2001). Regulations imposed by management generally have a spatial component either explicitly through time and area closures, or implicitly through allocation of quota to regions or to fleet sectors with different distributions.

Spatial management tools have been used to protect spawning aggregations, to reduce bycatch, or to meet other single-species objectives. In the past, fisheries science
tended to evaluate management performance with indicators based on non-spatial population dynamics models, even when the biology of the fish and the management tools used had a spatial component (Pauly et al., 2003). Application of such models may be sufficient if only the effect on the population is of interest (for example, when protecting a specific fraction of juvenile fish through gear restrictions or through a closed area).

In addition to sustaining fisheries yields, EBFM incorporates a range of new objectives related to sustaining the structure and function of ecosystems and their components (Pikitch et al., 2004). Because some components have a restricted distribution, their protection may require spatial management. Further, maintaining genetic diversity might require protecting some fraction of each spatially distinct sub-population of an exploited species (Gislason et al., 2000). Therefore, the use of spatial management tools such as marine protected areas (MPAs) is integral to EBFM (EPAP, 1999). MPAs may protect critical habitat from destructive fishing practices, provide insurance against unforeseen ecosystem impacts of fishing, and protect critical life stages of harvested species (Sumaila et al., 2000; Lubchenco et al., 2003). They may also assist in protecting biodiversity and hedge against management miscalculations (Allison et al., 1998; Lauck et al., 1998; Sala et al., 2002). Also the indicators to be used to evaluate such management measures must be explicitly spatial.

The increased use of spatial measures in achieving ecosystem and community-level objectives requires the incorporation of spatial analysis into the calculation of population level indicators, while non-spatial management measures such as catch and effort limits have to be evaluated in the context of the spatial measures taken. If indicators of yield and ecosystem health are derived from multispecies or ecosystem models, those models should also correctly account for spatial biological processes, objectives, and management tools. Here, we present a review of methods used to derive spatial indicators at the single-species and ecosystem level, with comments on useful practices and future areas for development, focusing on their practical use in fishery management.

Single-species approaches
Multi-box population dynamics models

Many species of harvested fish and shellfish are composed of multiple sub-populations that are genetically distinct and are segregated during at least part of their life cycle. If the spatial overlap between sub-populations is small, biology-based boundaries may be drawn to manage each unit (or stock) independently. Stock-based management is appropriate provided that management areas are defined correctly and migration between areas is limited, but the approach breaks down when management areas are defined by political boundaries (e.g. shark populations within the Atlantic EEZ of the USA and Mexico; McAllister et al., 2001) or by statistical areas with no biological meaning (Clay, 1996).

When there is evidence of migration between management areas, the total population may be split into a small number of boxes for stock assessment purposes. Migration rates between boxes may be estimated from tagging data, either independently or within the model used. For example, Porch et al. (1998) used conventional tagging data in combination with fisheries data in an integrated model to estimate migration rates between the eastern and western Atlantic populations of bluefin tuna. In such multi-box models, the population is assumed to be homogenously distributed and fully mixed within each box, and area-based MSY (maximum sustainable yield) reference points may be computed that take into account the long-term average abundance and distribution by age group over the different management areas (Apostolaki et al., 2003a). Multi-box assessment models are probably the simplest way to incorporate spatial management into the calculation of indicators.

MPA models

Unlike models used in designing terrestrial parks (Carr et al., 2003), which focus on maintaining critical habitat for key species, MPA models tend to focus on single-species population dynamics (see review by Gerber et al., 2003; but see Beger et al., 2003, for biodiversity-based methods for selecting MPA locations). Many of these are based on recruited fish only, although some incorporate larval dispersal. Apostolaki et al. (2002) developed a two-area, age-structured model for Mediterranean hake, which allowed for heterogeneity in the spatial distribution of fish. One area was assumed to become an MPA, and the existing effort was redistributed over the remaining area. The model showed that the effect of the MPA on spawning-stock biomass was positive or negative depending on the size classes protected. In general, models of single-species population dynamics indicate that the effectiveness of MPAs in rebuilding or maintaining populations of the species of interest depends on the rates of immigration and emigration, and on the fishing effort outside the reserve (Gerber et al., 2003). They also show that the long- and short-term effects on yield depend on the migratory behaviour of the fish; the response of the fishers; the biological characteristics of the species (i.e. growth rate); and the size, shape, and location of the MPA (Daan, 1993; Bohnsack, 2000; Acosta, 2002; Apostolaki et al., 2003b).

The models vary in spatial resolution; some have grids of cells within and around the reserve, and some simply model “inside” and “outside”.

Spatial analysis of fishery-dependent data

Spatial heterogeneity is often accounted for through standardization of abundance indices. Whether from
surveys or from the fishery, indices of catch rate (catch per unit effort, cpue) vary geographically. Because survey data are geo-referenced, unbiased indices of abundance may be derived, after accounting for spatial autocorrelation (Simonds, 2003), shifts in distribution (Albert et al., 2001) and other spatial patterns and processes. For fishery cpue data, spatial processes are generally modelled to obtain an overall index of abundance. For example, cpue indices used for North Atlantic swordfish (Xiphias gladius; Anon., 2003) are generally standardized by means of a generalized linear model (GLM) that estimates the effect of area, season, and year. The year effect is then assumed to be an unbiased estimate of the trend in abundance. With the coarse spatial resolution applied (the North Atlantic being divided into 6–12 regions), large-scale patterns in spatial distribution may be captured. However, this methodology cannot capture small-scale impacts of management measures, and processes at these smaller scales may introduce bias in the estimated trend. For example, part of the US EEZ was closed to longline fisheries in 2001, including the swordfish fishery (Cramer, 2003). To remove its effect from the year effect, the sets in the US longline data were classified according to whether they were taken inside or outside the area closed in 2001, and this closed-area factor was included in the GLM (Ortiz and Scott, 2003). Although the analysis may remove effects of structural differences between closed and non-closed areas (e.g. in terms of habitat), it cannot remove possible bias caused by changes in fishing effort around the edge of the closed area.

The problems with cpue data are well known, and they include quality issues as well as changes in gear and target species over time, all of which make fishery-independent data preferable for assessment purposes. If their use cannot be avoided, however, applying a greater spatial resolution might make it possible to identify, and thereby to remove, some bias. For example, Myers and Worm (2003) showed that catch rates in an expanding pelagic longline fishery were highest along the edge of its range, an effect that would not be captured by breaking up the North Atlantic into a limited number of large regions. This is essentially a problem of missing data, caused by the fishery initially not sampling the entire distribution range of a population, leading to potential bias in estimated trends (Walters, 2003). When cpue data are geo-referenced, it may be possible either to extract an unbiased trend (Salthaug and Aanes, 2003; Walters, 2003), or to find spatially explicit estimates of abundance and fishing mortality (Booth, 2000; Verdoit et al., 2003). For example, Kirchner and McAllister (2001) showed for a highly aggregating fish species off Namibia (orange roughy, Hoplostethus atlanticus) that more accurate indices of relative abundance could be obtained by mapping the annual area covered by the spawning aggregations, then utilizing this information to estimate average catch rates per fishing ground. Fine-scale analyses were made possible by the availability of precise data on depth, location, and biomass extracted by each commercial trawl tow on each fishing ground in each year. The relative trends in abundance obtained differed considerably from those obtained by the conventional and incorrect approach of assuming stationarity in distributions over time. Increased understanding of the limits of fish dispersal during the early years of this very recent fishery led to separate management of each of the four different orange roughy fishing grounds within Namibia’s EEZ (Kirchner and McAllister, 2001).

Spatial models of fishing effort

Stock assessment rarely includes spatial analyses of effort distribution, although the need for it has long been recognized (Hilborn, 1985). Such analyses are needed particularly for designing strategies that use both spatial and non-spatial management tools. The effect of a closed area on the ability of a population to rebuild, for example, depends on the effort in the area before the closure as well as knowledge of where the displaced effort will go. Better predictions should lead to better MPA design.

Models of fisher behaviour (Sanchirico and Wilen, 1999, 2001; Babcock and Pikitch, 2000; Wilen et al., 2002) have been based mainly on the assumption that fishers choose locations that maximize their expected profit from a fishing trip. For example, Wilen et al. (2002) developed a model of a dive fishery for sea urchins, in which the diver’s decision about whether and where to dive could be predicted from information on weather, catch rates, and prices. This bi-economic model predicted the impacts of proposed closed areas and size limits that were markedly different from those predicted by simpler models with their ad hoc assumptions about redistribution of effort. Spatial models of fish dynamics allow more accurate prediction of the effects of envisaged management measures. The current effort distribution is the result of each fishing unit’s response to the management measures taken, market conditions, and fish abundance and distribution. As Wilen et al. (2002) noted, an individual fisher’s economic decisions, rather than aggregated effort, have to be modelled to be able to predict the consequences of future management action. Also, the spatial dynamics of the fish and the spatial dynamics of the fishery interact, so effort redistribution after a closed area is established depends partly on how fish move around (Sanchirico and Wilen, 1999). Finally, better knowledge of how fishers select fishing locations might lead to improved understanding of the relationship between cpue and abundance (Booth, 2000; Kirchner and McAllister, 2001).

Ecosystem-level models and indicators

Metrics of ecosystem health and impact of fisheries on ecosystems may be classified (Rice, 2000) as: (i) species diversity indices, (ii) ordination methods, (iii) aggregate indicators of ecosystem status, and (iv) “emergent
property”. Done and Reichelt (1998) suggested diversity metrics weighted by desirable characteristics of species in an ecosystem, such as trophic level. Ordination methods such as principle components analysis (PCA) reduce a matrix of species observations to a small number of orthogonal gradients, and could be used to quantify the effects of fishing on fish communities (Rice, 2000).

Aggregate indicators of ecosystem status include size spectra and biomass curves (Bianchi et al., 2000). Emergent property metrics are derived from ecosystem models, such as mean trophic level of the catch from mass-balance models, or stability and resistance to perturbation of a foodweb model (Rice, 2000). Others have proposed suites of indicators, including habitat, biodiversity, and overfishing criteria (Murawski, 2000; Brodziak and Link, 2002). Some of the indicators proposed are only general measures of ecosystem health; others have potential to develop decision rules so that a particular value of the indicator would require specific management action (Gislason et al., 2000).

Empirical indicators such as diversity indices could include a spatial component. For example, the definition of ecosystem overfishing might require that a fraction of the management area not be harmed by fishing, while the rest of the area may experience some ecosystem change through fishing activity. Nevertheless, multispecies and ecosystem models seem to have the most potential for producing spatially explicit indicators of ecosystem impacts of fishing. As with single-species models, one possible approach is to use spatial analysis to derive regional indices of abundance and other inputs to multispecies models. For example, Bulgakova et al. (2001) used kriging to fill in missing data and hence derive unbiased estimates of partial stomach contents at the stock level as inputs to multispecies virtual population analysis (MSVPA) for the Barents Sea. Multispecies models with spatial structure have also been developed. Among the ecosystem models reviewed by Robinson and Frid (2003), nearly half included at least some spatial component.

Spatial multispecies fisheries models do not necessarily include trophic interactions between species (Wu and Levin, 1997; Walters and Bonfil, 1999; Pelletier et al., 2001; Mahevas and Pelletier, 2004). The simulation model developed by Pelletier et al. (2001) and Mahevas and Pelletier (2004) includes population dynamics and migration of multiple species and fishing effort allocated to “métier” (defined as a combination of target species, fishing area and season, and gear). This model may be used to evaluate the potential consequences of spatial management measures, assuming that interactions among species are negligible. Walters and Bonfil (1999) fitted a spatial multispecies age-structured model to British Columbia groundfish data. Spatial patterns in catch rates of each species were extrapolated from observer data, after which the area was divided into a number of fishing grounds. Effort was allocated according to a “gravity” model in which fishing grounds with higher catches for lower costs are more attractive to fishers. The model was used to examine possible consequences of the closure of specific fishing grounds.

Spatial models of predator–prey dynamics have been developed for several ecosystems, e.g. for krill (Euphausia superba) and their seal and penguin predators in the Southern Ocean (Constable et al., 2000), and for cod (Gadus morhua) and capelin (Mallotus villosus) in the Barents Sea (Tjelmeland and Bogstad, 1998). A multispecies equivalent of the multi-box population dynamics models has been developed using MSVPA (Köster et al., 2001). MSVPA includes predator–prey dynamics to estimate the rate of predation mortality at age, based on stomach content data. Köster et al. (2001) developed an area-disaggregated MSVPA representing three subdivisions of the Baltic Sea, which they assumed to contain unit stocks of cod, the predator, and herring (Clupea harengus) and sprat (Sprattus sprattus), the prey. Although their implementation did not incorporate migration because of lack of information, the model might, in principle, be used to derive area-specific indicators that incorporate both trophic interactions and movement. As with single-species models, the spatial boundaries, and relevant movements between them, have to be identified correctly, for example, if shifts in oceanographic conditions cause shifts in distribution (Brander, 2005).

Ecospace, in the Ecopath/Ecosim family of models (Walters et al., 1999; Pauly et al., 2000) includes trophic interactions, migration, and effort redistribution. Ecospace breaks the Ecopath/Ecosim ecosystem model up into a grid of spatial cells with user-defined habitat and costs of fishing, allowing for migration between adjacent cells. Costs may, for example, be related to distance from port, which itself has an effect on the distribution of fishing pressure. Ecospace simulations indicated that the effectiveness of an MPA in terms of protection depended strongly on the assumptions made about fish migration and effort redistribution in the cells around the MPA (Walters et al., 1999).

These ecotrophic multispecies models require many more data than single-species models. Also, owing to the complexity of the processes included, the uncertainty in the results obtained is difficult to quantify. Nevertheless, their application has demonstrated the importance of certain processes in evaluating the impact of spatial management that may be missed in simpler models. Specifically, the effect of fisher choice of fishing grounds on species composition of the catch is such a critical element (Walters et al., 1999; Walters and Bonfil, 1999; Mahevas and Pelletier, 2004). System-level models are also useful as operating models for evaluating management strategy (Sainsbury and Sumaila, 2003), because they allow evaluation of alternative management strategies as well as of alternative hypotheses about ecosystem processes. In principle, reference points related to yields might be
derived from such models, as well as general indicators of ecosystem status, although as yet there have been few examples of this. For example, Ecospace could allow comparison of the mean trophic level of fish inside or outside an MPA as an indicator of the general impact of fishing. Multispecies equivalents of MSY reference points can also be derived from such models (Witherell et al., 2000).

Mapping and spatial analysis

Many methods of spatial analysis with potential for deriving indicators for EBFM may be derived from other disciplines. In the terrestrial environment, spatial management measures are common, and the efficacy of parks is generally measured in terms of the fraction of various types of habitat protected (Carr et al., 2003). Consequently, spatial analysis is more sophisticated in terrestrial than in marine science. For example, Rouget et al. (2003) developed a geographic information system (GIS) to identify characteristics of habitat that would be of importance for maintaining ecological and evolutionary processes indefinitely (e.g. ecotones, migration corridors between habitat types), concepts that are only now beginning to be considered in the marine environment. Part of the reason why marine ecology is lagging behind in this respect lies in the fact that the marine environment is spatially more complex than the terrestrial one. The ocean is a 3-D space, and relevant oceanographic features such as currents and eddies move on time scales relevant to fisheries. Thus, a pelagic marine GIS represents a 4-D problem (Meaden, 2004). The population focus of classical fisheries science, in contrast to the habitat-focused conservation efforts on land, has also contributed to the lack of interest in spatial analyses.

Although the need for spatial analysis in fisheries is well recognized (Nishida and Booth, 2001; Pauly et al., 2003; Booth and Wood, 2004; St Martin, 2004), developing a marine GIS is much more labour- and data-intensive than any of the classic tools. Development of regional and global GIS databases has been reviewed by Valavanis (2002). Spatial analysis is commonly used in nearshore environments for benthic habitat classification (Battista and Monaco, 2004). In the US, the legal requirement to protect “essential fish habitat” has led to much work in this field (Allee et al., 2000; Rosenberg et al., 2000). Mapping is useful for identifying areas that would be suitable for protection from impacts of destructive fishing gear (Fogarty and Murawski, 1998) and to protect nursery grounds. Spatial processes in the pelagic environment are intensively studied in physical and biological oceanography, and such information is sometimes used in fisheries management. For example, models of fine-scale eddy formation are used to predict year-class strength of fish that spawn in the pelagic environment (Megrey et al., 1996; Polovina and Howell, 2005). EBFM would be facilitated by further integration of oceanography with fisheries science, particularly if oceanographic processes strongly influence population dynamics (Bakun and Broad, 2003).

From an EBFM perspective, the availability of geo-referenced data on habitat, resource distribution, and fishing effort, and the increasingly sophisticated methods available in GIS for visualizing and processing these data make it possible, at least in principle, to derive spatial indicators of fishing impact. Useful spatial analyses include: (i) interpolating point or line data to develop detailed contour diagrams; (ii) overlaying data layers to measure spatial overlap; (iii) buffering closed areas and other spatial features; and (iv) attributing data on bathymetry and slope from maps to sampling stations (Bakelaar et al., 2004). This allows one to ask questions that cannot be addressed with crude measures of space based on statistical areas, such as: “what is the effect of distance from a closed-area boundary on cpue?” or “what bathymetric and oceanographic conditions are associated with each species in the catch?”

GIS and other types of spatial analysis have been used in conjunction with population dynamics modelling, and as a decision-support tool in management. Valavanis et al. (2002) developed a GIS of the cephalopod fishery in the eastern Mediterranean, which included habitat and oceanographic data as well as geo-referenced fishery data. Maury and Gascuel (1999) developed a GIS-based simulation model to study the impact of an MPA given seasonal migration of fish. Lindholm et al. (2001) used a dynamic model to study the link between survivorship of post-settlement juvenile cod and spatial variation in habitat complexity. The model simulated habitat changes based on fishing activities, and was used to evaluate the potential of an MPA to enhance recruitment success. Ault et al. (1999) developed a spatial multi-stock model of fish and shrimp population dynamics that included a hydrodynamic circulation model as well as habitat information. Spatial modelling methods have also been used to examine economic and social questions about fisheries. Scholz (2003) developed a GIS of fishing locations cross-referenced with the port of origin to determine the economic impact of a proposed closed area on fishing communities along the coast.

Ecosystem-level indicators based on spatial analysis are only beginning to be developed. Fréon et al. (2005) have derived GIS-based indicators for the southern Benguela that include a spatial index of biodiversity, the exploited fraction of ecosystems, and the mean distance of the catch from the coast. Other potential indicators include the fraction of each habitat type that has some desirable characteristic, or the area of good fishing grounds within a certain travelling distance of a major port. GIS-based methods could also be used to improve understanding of single-species and multispecies population dynamics, and fleet dynamics. For example, analyses of geo-referenced cpue data (Booth, 2000; Kirchner and McAllister, 2001).
can improve estimates of fishing mortality and abundance trends.

New technologies such as vessel monitoring systems (VMS) and the development of inexpensive and easy-to-use GIS software are making geo-referenced data analyses more practical. They are potentially useful both for deriving observational indicators and for developing inputs for functional models. For example, the functional links between habitat quality and fish population dynamics are only beginning to be understood. Understanding the spatial components of ecosystem processes and fleet dynamics will allow new indicators based on spatial measures (Fréon et al., 2005) to be derived, as well as providing useful inputs to single- and multispecies models.

Conclusions

Spatial management tools, if implemented effectively, can greatly improve fishery management (Sainsbury et al., 1997). To design spatial EBFM tools and monitor their effectiveness, however, spatialized ecosystem indicators and modelling tools are required. While considerable work has been conducted that addresses the problem of developing such tools, more work is required to bridge the current gap between the availability of a variety of spatial management tools and the paucity of operationally sound spatialized ecosystem indicators.

The indicators, based on single-species population dynamics models that are used to evaluate management objectives related to abundance and yield, must also incorporate relevant ecological processes, including spatial ones. Detailed analyses based on geo-referenced cpue data should help track more accurately trends in spatial distribution of fishing fleets and fish abundance. Spatially explicit models of fish population dynamics and fishing activity have been developed to evaluate the conditions under which spatial management tools may work or fail. To develop new reference points such as MSY for given spatial management units and associated management advice, the models developed will have to be fitted to available data, and uncertainties in parameters and model structures will have to be taken into account. Improvements in the resolution of fishery-related data and understanding of area-dependent dynamics of species should support the development of such reference points. Better understanding of fisher behaviour on the fishing grounds may also contribute to a better design of new management measures that take into account the predictable responses of fishers.

There is a need to integrate the knowledge and skills of landscape ecologists who routinely use GIS with those of fisheries scientists who use sophisticated population dynamics models and statistical tools for management strategy evaluation. Such a synthesis would aid the design of spatial management measures, prevent bias in trends caused by spatial heterogeneity, and support the development of EBFM.

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