

# Using oceanography for fisheries stock assessment and management: A review

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## Abstract

Fisheries stock assessment and management has been criticized for failing to account for oceanographic processes. To examine this failing we review the use of oceanographic data in fisheries stock assessment and management. It is clear from the abundant research that fisheries scientists and managers are well aware of the role that oceanographic processes play in controlling fish populations. Debate about the relative roles of fisheries versus the environment in determining the abundance of fish stocks has persisted for decades. There are numerous examples of academic exercises developing methods to identify relationships between population dynamics and oceanography, integrate oceanographic data into stock assessment and management, and to evaluate the advantages of using oceanographic data, but there is a lack of successfully implemented examples in the real world. Unfortunately, the understanding of the mechanisms involved, the available data, or the large scale correlations are often too poor to provide any substantial benefits. In most cases, statistically significant correlations between population dynamics and population processes break down when tested against new data. This has led to advocating for direct monitoring or developing management strategies that are robust to the variation rather than determining the relationships between population dynamics and oceanographic processes. The few successfully implemented examples mainly relate to predicting the spatial distribution of a fish stock. Therefore, use of oceanographic data to determine dynamic spatial closures to reduce bycatch appears to be the most promising area of research. The availability of fine spatial and temporal scale oceanographic data from remote sensing and oceanographic models, vessel monitoring systems, and electronic tags allow research on more appropriate scales, which may lead to improvements in the near future. However, it would be wise for researchers and managers to be realistic about the benefits of using oceanography in fisheries stock assessment and management so that the most benefit can be made of limited funding for data collection, monitoring, and research.

## Introduction

We review the use of oceanography for fisheries stock assessment and management, provide examples of and reasons for observed successes and failures, and provide thoughts on the future integration of oceanographic data in analyses of resource status and management.

Fisheries scientists have long debated the relative importance of fishing on spawning stock biomass and oceanographic factors as determinants of recruitment to fisheries (Hjort, 1914; Platt et al. 2007). Discussions of causes for declines in major fisheries usually revert to this debate (Walters and Parma 1996), and effective fisheries management requires discrimination between the effects of the environment and the effects of fishing (Hampton et al. 2005). Fishery impact analysis that separates population change due to fishing from that due to other causes (Wang et al. 2009) suggests that changes arising from natural causes, such as variability in oceanographic conditions, can be as large or larger than those caused by fishing (Sibert et al. 2006).

The use of oceanographic data has improved our ability to anticipate and define the spatial and temporal distributions of fish. Prior to the mid-20<sup>th</sup> century, most fisheries operated in the near-shore regions of the oceans. It was also recognized that carbon production [productivity] of the oceans should be at least equal and likely more than that of the land (Riley 1944, Steemann-Nielsen 1952), which implied that there remained untapped resources in the oceans.

Focusing on the mid-and lower latitudes of the Pacific Ocean, Sette (1955) hypothesized that "... in situations of ... modified vertical stability there would be chemical enrichment of the euphotic zone, supporting increased biological productivity and large stocks of fish, just as is true wherever there are mechanisms for enrichment in the marginal seas flanking the continents." In what he described as the "first attempt to focus scientific effort of nearly adequate scale on this problem," Sette used his knowledge of oceanography to predict and subsequently to demonstrate the spatial-temporal progression of enrichment to phytoplankton to zooplankton to larger predators. In so doing, he documented the existence and potential for production from the then unexploited tuna resources of the central and eastern regions of the mid-Pacific.

With advances in technology, particularly in satellite-based earth observation systems, more recent applications of ocean data have used remote sensing data from satellites to predict the spatial distribution of stocks, in order to increase the catch of target species (Santos 2000); and to reduce by-catch (Hobday et al. 2009).

Ocean conditions may impact food supplies that influence survival, growth, age at maturity, and fecundity, as well as the spatial distribution of adult fish. There has been less success in using ocean data in models that predict population parameters and processes; such as recruitment, which is a product of many early life events that are not well understood (Walters and Collie 1988). Survival through early life stages is believed a major controlling factor in the number of individuals that finally make it into a fishery and become available for human consumption. These stages may be particularly vulnerable to oceanographic processes, for example to advection or mixing that takes individuals to areas of abundant food sources or brings the food to them.

Oceanic variability occurs on many time scales, from diurnal to seasonal, inter-annual, decadal, multi-decadal and longer (King and McFarlane 2006). Naturally occurring large-scale long-term oceanic regime shifts can have major impacts on biomass of fish stocks. Regime shifts are evidenced [after they occur] as changes in major oceanographic parameters from one state to another over a time period shorter than that period over which the conditions exhibit some stability. Among other things, they are believed to be the cause of switching between anchovy and sardine dominance in ecosystems of the Pacific Ocean (Chavez et al. 2003) and between low and high productivity periods of yellowfin in the eastern Pacific Ocean (Maunder and Aires-da-Silva 2008).

Fisheries stock assessment and management has been criticized for failing to account for oceanographic processes (Basson 1999). The criticism derives from the numerous examples supporting population impacts driven by oceanographic processes (Tomczak 1977; Sharp and Csirke 1983; Caddy and Gulland 1983; Sund et al. 1981; Keyl and Wolff 2008) and the failure to account for these processes in fishery stock assessment models and harvest rules (Sharp 1995; King and McFarlane 2006). Much of the criticism has been directed at the perceived lack of biological realism in contemporary stock assessment. Parsons (1996) states “Finally, there is a paramount need in the future science of fisheries for factual data on the environment of fish ... and fewer theoretical assumptions derived by scientists working with computers, out of touch with Nature.”

Fisheries and ecosystem-based management does need to recognize and accommodate variation on these many scales, and it is expected that integrating measures and information on oceanographic processes into fisheries stock assessment may lead to more reliable estimates of the status of resources and improved management. However, the availability and reliability of these data are strongly linked to developing technologies. Thus the time series of data from fisheries, and from oceanic and environmental processes, are generally now available only for only a few decades for the most intensively monitored fisheries, and for only a one or two decades for what are considered by many the most important oceanographic measures.

Covariates based on oceanographic data have been used to apportion temporal variability in population or fishing processes (Maunder and Watters 2003), and to improve predictions of future abundances or catch rates. Accounting for the influence of oceanographic processes on catch rates can help avoid biases when extracting abundance information from catch rate data (Hinton and Nakano 1996). Knowledge of oceanographic effects on fish distributions may be useful to improve estimates from abundance surveys (Pinhorn and Halliday 1985). Evaluation of long-term climate change on oceanographic processes and the consequent impact on fish populations is an active area of research (King and McFarlane 2006). However, uncertainty in climate change models, coarse climate model resolution, and uncertainty in the mechanisms of how climate affects fish stocks limit the robustness and precision of projections (Stock et al. 2011). This becomes even more complicated when the whole ecosystem and its interactions are taken into consideration (Watters et al. 2003).

Unfortunately, current scientific understanding and available data are inadequate to support models with detailed biological realism, and it is not clear that such models would reduce overall uncertainty in estimates of stock status and trends. Due to the historically poor prediction performance of population

dynamics models and analyses that incorporated correlations to oceanographic parameters (Myers 1998; Myers et al. 1995), stock assessment scientists generally promote harvest strategies that are robust to uncertainty in oceanographic forcing (Walters and Collie 1988; Walters and Parma 1996). Managers need to either develop harvest strategies that are robust to uncertainties, or they need to invest in biological studies, monitoring and data collection from fisheries, and collection of oceanographic data at scales relevant to biological and fishing processes in order to reduce uncertainty introduced by scale mismatch that leads to poor correlation of oceanographic data and population dynamic processes (Basson 1999).

Previous research may have been conducted at inappropriate scales, due to the “limitations of ships as oceanographic observation platforms” (Platt et al. 2007). Thus, previous decisions to not use oceanographic data in fisheries stock assessment and management have perhaps been prudent given the then current understanding of ocean environments. However, today we may find that recent developments in oceanographic data availability and analysis lead to better understanding of the mechanisms underlying variability in biological and population parameters and to improved explanatory power of fisheries stock assessment models and management recommendations.

Comprehensive oceanographic data on fine temporal and spatial scales from satellite remote sensing (Santos 2000), general circulation models, and fish habitat preference and behavioral data from electronic tags (e.g. Schaefer and Fuller 2002 and Domeier 2006) now allow fisheries research to be conducted on scales that are closer to those of the mechanisms being studied. Yet it remains that the principal shortcoming in oceanographic data is that the sample design and data collection are driven by modeling and analyses of climate and earth processes. This is unlikely to change until expenditures by fisheries managers are sufficient to fund experiments and data collection as value-added products that do not add risk to primary missions in oceanographic and atmospheric research.

## Oceanographic data

Analyses of earth processes and climate drive the experimental design and collection of principal sources of data from the oceans and atmosphere (e.g. Wyrтки et al 1981, Sprintall and Meyers 1991, McPhaden et al. 1998). The spatial and temporal scales of interest in these studies are significantly greater than those of the relatively small-scale processes impacting individual animals and their aggregations. Complexity is added by the fact that the scales of variability of oceanographic parameters are not constant across ocean basins. A good example of this is shown by comparing the results of studies to design oceanographic data collection networks in the Pacific for optimal interpolation of temperature fields. White and Bernstein (1979) found that in the north Pacific [30°N to 50°N], variability in temperature fields was dominated by signal at a temporal resolution of 10 months; and at spatial resolutions of the “mesoscale” (~300 km) west of 175°W, due to presence of baroclinic eddies or waves, while larger scale variability dominated east of 175°W. This E/W difference translated into required sample-station placement for optimal interpolation at about 50 km intervals to the west of 175°W, and at about 200 km to the east thereof. Similar studies in the tropical Pacific [18° S to 18° N] (Meyers et al. 1991) found that the decorrelation scales for the median depth of the 20°C isotherm were limiting, with temporal decorrelation scale of two months, and spatial decorrelation scales of 3° latitude and 15°

longitude. In the tropical regions, therefore, sample-station placement needed for optimal interpolation was at 1.5° latitude and 7.5° longitude.

The mismatch in scales of interest in fisheries and oceanographic research requires compromising detail in either the fisheries or the oceanographic data, and thus frequently analysts develop statistics which aggregate the data from fisheries to scales matching the resolution of oceanographic data.

The methods traditionally used to collect oceanographic data (e.g. vessel, buoy, and pier based sampling) are generally spatially or temporally restricted. For example, the “Shuttle Experiment,” designed to study equatorial current systems and develop a basis for their monitoring, was an 18-month observation of temperatures obtained from expendable bathythermographs (XBTs) deployed by ships of opportunity (Wyrski et al. 1981). Meyers et al. (1989), using the method of optimum interpolation and data from XBTs, designed a monitoring system for the ocean areas north of Australia. McPhaden et al. (1998) reported on the Tropical Ocean-Global Atmosphere (TOGA) program, a 10-year study “... of climate on seasonal to interannual time scales [requiring the] accurate determination of basin scale fluctuations in surface winds, sea surface temperature (SST), upper ocean heat content, near-surface currents, and sea level in the tropical Pacific ...” in order to characterize variability of the El Niño – Southern Oscillation. TOGA depended on data from tide gauges, XBT observations from ships-of-opportunity, drifting buoys, moored arrays; such as the Tropical Atmosphere Ocean (TAO) array; and increased availability of data from satellites. McPhaden et al. recognized that “... large areas of the tropical Pacific would still be poorly sampled and that important [pan-Pacific basin] processes ... would not be well resolved.” Perhaps the most important caution they present for analysts of fisheries data is in their note regarding problems in acquisition of oceanographic data from satellites: “For example, launch of the U.S. National Aeronautics and Space Administration’s scatterometer (NSCAT) for surface wind velocity estimates, originally scheduled for 1989, has been delayed until after the end of TOGA; and there was a 2-y hiatus in satellite sea level altimetry measurements between the end of the U.S. Navy’s Geodetic Satellite (GEOSAT) mission in 1989 and the launch of European Space Agency’s Environmental Research Satellite (ERS-1) in 1991.”

With developing technology, satellites have provided high resolution data, but satellite missions have not been flown to obtain data according to sample designs for fisheries analysis. Missions are generally specific to studies and should not be considered operational data, because they are not systematically obtained with assurance that they will be available beyond the end of the study period. The high resolution of satellite data may make it suitable for some analyses of fishing and fishing processes at the level of individual operations of fishing gear, however, the inability to project the availability of the data into the future makes it generally unsuitable for direct use in assessment models and management applications.

There are instances when oceanographic data may be well suited to investigations of fish and fisheries. A swordfish carrying an archival tag fortuitously passed through the area where an oceanographic research vessel was conducting operations and data collection, providing the means to not only more clearly define the swimming path of the individual, but also to determine and validate behaviors observed in the data from the tag, behaviors that without the vessel-based data would have been, if

recognized, simply speculation (Takahashi et al. 2003). Cases like this represent the rarest in exceptions of synoptic collection of oceanographic data and fisheries observation at high resolution.

Though ocean and atmospheric data may not be available on the scales of observations or proposed mechanisms, still it may be possible to develop proxies and to predict future events. MacKenzie and Koster (2004), using data on recruitment of sprat (*Clupea sprattus*) in the Baltic Sea that had been collected over a 45-year period, demonstrated that large-scale measures of climate variability, ice coverage, and water temperature could be used to forecast recruitment to the population.

Analysts of data collected to understand earth processes and climate have developed general circulation models (GCMs) of the atmosphere and oceans. These models provide estimates of oceanographic and atmospheric parameters at relatively high resolutions over long periods of time. They are intended to not only describe but to provide the basis of prediction of ocean and atmospheric parameters at various levels of resolution and precision. GCM model output provides alternatives to direct observations, providing for analysis of “synoptic” oceanographic and fisheries data. Judicious use of these model outputs is necessary, because individual models are generally tuned to specific ocean regions, which may lead to inaccuracies and high variability associated with outputs for regions outside the principal focus of the model.

The most common use of oceanographic data in fisheries occurs with the use of derived products, and perhaps most often they are the outputs from GCM models, but at times fisheries analysts construct derived environmental data products specific to their region of study. Hobday et al. (2011) include in their analysis of tuna habitat a parameter constructed as a reanalysis and spatial interpolation of data from Argo floats (<http://www.argo.ucsd.edu/index.html>) and CTD surveys. Neither of these data sources is obtained on the level of resolution of fisheries. For example, the design placement of Argo floats in the global oceans array is at three degrees of latitude and longitude. This design was chosen to provide resolution of temperature and salinity fields on the order of 200-300 km (Roemmich et al. 1998). These data do not directly provide information to analyses of fisheries data at higher resolutions.

Acoustic tracking and archival tags has been used to measure the environmental preferences of many marine species (see e.g. Holts and Bedford 1993, Goldman and Anderson 1999, Dagorn et al. 2001, Schaefer and Fuller 2002, Domeier et al. 2005, Kraus et al. 2011). These electronic tags store data on the ocean conditions frequented by individual animals. The data are collected and compiled, after recovery of the tag or transmission of the data to researchers via satellite uplink, and it is used to understand the conditions preferred by and limiting the distributions of these species. However, in a possible turn of events, it has been suggested that such tags may provide data suitable for use in analyses of climate change. McMahon et al. (2005) were able to validate the ocean temperature data collected from tags placed on leatherback turtles (*Dermochelys coriacea*) with data from the Argo array in the Atlantic Ocean, which suggests that at least when latitude and longitude are well known for archival tag data, those data may provide oceanographic observations in “... remote and inaccessible locations.”

## Predicting catch and abundance using environmental data

Oceanographic processes will usually affect the spatial-temporal distribution of a stock, and oceanographic data may be useful to predict distributions. This is particularly true for highly mobile species that have specific physiological constraints, habitat preferences, or congregate in areas of high prey abundance which are identifiable using environmental data. The distribution of ocean parameters affects the spatial distribution of adults of many species far more than any other factor. A variety of methods (e.g. GLM, GAM, GLMM, regression trees) that include oceanographic covariates can be used to predict the spatial distribution of abundance (see Venables and Dichmont 2004). The methods could also be extended to three dimensions by incorporating depth. The use of oceanographic data to identify regions of expected high abundance or catchability is a common practice, since it has direct economic benefit through increasing fleet efficiency (Santos 2000). It can also be used to avoid regions of expected high catches of by-catch species (Hobday et al. 2009). Use of predicted spatial distributions of oceanographic parameters for management may be problematic, because in most cases these data may not be available at required scales on a real-time basis.

There are numerous examples of general patterns of fish distribution associated with oceanographic parameters. Variations in ocean-color, which is related to primary productivity, may explain a large proportion of the variance in yields of resident fish stocks (Ware and Thomson 2005; Platt et al. 2007). Ocean eddies and fronts create conditions for relatively high productivity and may act as concentrators of food sources for predators. Dell et al. (2011) found that high yellowfin tuna catch was associated with elevated eddy kinetic energy, a shallow surface mixed layer, and relatively high concentrations of chlorophyll in the Tasman Sea; findings not unlike those that have been made by multitudes of studies examining the relationships of ocean parameters and the distributions species.

Fisheries scientists frequently include covariates of time, generally month; and space, generally latitude and longitude at 1-degree or 5-degree resolution; in models that also include oceanographic parameters, only to find that in many cases the spatial covariates explain as much variation or more than is explained by oceanographic covariates. This should not be surprising, because though not constant, the temporal and spatial decorrelation scales of ocean parameters are much greater than those of the fisheries, and they thus appear relatively constant at these scales.

## Standardizing CPUE using environmental data

Physiological constraints and preferences for ocean conditions of temperature, oxygen, salinity, or other factors alter the spatial and depth distribution of fish stocks, affecting their availability to fishing gear (Hinton and Nakano 1996, Platt et al. 2007).

In analyses of stock status and trends, it is assumed that some measure of catch-per-unit-effort (CPUE) is proportional to abundance. Standardizing CPUE is done to remove the influence of factors other than abundance on trends in time series of CPUE. This is one of the most common analyses performed in fisheries stock assessment (see Maunder and Punt 2004). Numerous methods have been used to standardize CPUE; for example general linear and additive models, general linear mixed models, and regression tree analysis. The most common approach is to apply a multiple linear regression to the log-transformed CPUE (Maunder and Punt 2004, Venables and Dichmont 2004). Standardizations include

the categorical variable year (or other measure of time) as one of the explanatory variables, and it is the coefficients of year that are used as an index of annual relative abundance of a stock. A key underlying assumption is that the standardization has accounted only for variability not attributable to annual changes in abundance. These indices are then used as inputs to stock assessment models. The standardization of CPUE data can also be included directly in a stock assessment model to facilitate the propagation of uncertainty in the estimates of relative abundance into the assessment results (Maunder 2001).

CPUE standardization for tunas and billfishes involves large numbers of observations and even larger numbers when information from individual operations of fishing gear are used in an analysis. In either case, independent variables included in standardization models may be statistically but not practically significant. Judicious use of such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Burnam and Anderson 1998) for model selection can reduce the tendency to include independent variables and covariates that are not of practical significance.

The main assumption in CPUE standardization is that variation in CPUE attributable to whole stock abundance is only accounted for in the year (or other relevant variable used to index abundance) effect and not by other explanatory variables included in a model. It is key that independent variables included in a model not include variables which may be aliased with changes in abundance. Aliasing may occur when independent variables carry information on the temporal scale of the standardization. Any variable that is annual in nature may explain some of the variability attributable to annual variation in the abundance of the whole stock. For example, the ENSO (El Niño-Southern Oscillation) index is available at annual resolution. When conducting a standardization that provides an annual index of abundance, the ENSO index at annual resolution should not be included in the model, lest variability in abundance be accounted for by variation in the index. It is more appropriate to use data, including oceanographic, that is on the same spatial and temporal scale as the CPUE observations, which may require summarizing data, and/or duplicating data for multiple CPUE strata in a model. For example, rather than averaging across space and time to create an annual oceanographic covariate, the oceanography should be used on a monthly 1x1 degree square, if that is the resolution of the CPUE data.

A more mechanistic approach to modeling the influence of environmental, behavioral, and physiological constraints on CPUE was developed by Hinton and Nakano (1996). The method was first applied to longline CPUE for blue marlin. Analyzing longline CPUE data is complicated by the fact that the hook on which each fish is caught on is not known: only the total number of fish that are caught in a longline set is recorded. Taking into account the oceanographic conditions at the depth in which each hook is fished, the method essentially inversely weights the fishing effort [each hook] by the habitat quality where that fish is caught. The habitat quality reflects the likelihood of encounter of the species based on any number of environmental, behavioral, and physiological constraints, e.g. as might be calculated from observed frequencies using archival tag data. Evaluation of deterministic applications of the method (detHBS) indicated that the habitat preference data from relatively few archival tags collected from only a few locations generally provided inadequate models of habitat quality (Maunder et al. 2002), but that the model performed well when underlying assumptions were met (Goodyear 2003).

The poor performance of detHBS might be due to inaccuracies in the longline gear model (e.g. ignoring current induced shoaling) used to calculate the fishing depths of the hooks; the difference in resolution of the habitat preference (the fishes immediate surrounding) and the oceanographic data (large scale temporal and spatial averages); or that the habitat preferences based on archival tags might also include non-feeding habitat. Given the inability to clearly identify the reason for poor performance, the statistical version (statHBS) was developed (Maunder et al. 2006). In statHBS estimated habitat preferences are derived from the CPUE data. In other analyses of CPUE, a modified neural network was applied to implicitly allow more flexibility in the gear model, but it did not provide a substantial improvement over the standard GLM approach (Maunder and Hinton 2006); and Bigelow et al. (2002) used GAMS incorporating oceanographic data to standardize CPUE.

One deficiency of most applications of current methods used to standardize CPUE is that they do not account for changes in total available habitat with changing oceanographic conditions. If the total available habitat shrinks, then the chance of catching a fish in that habitat will increase. Standardizations need to be adjusted so that the sum of the total habitat in a time period is calculated and the CPUE adjusted for that total.

## Processes

It is undeniable that population processes are influenced by local oceanographic conditions. Laboratory experiments have clearly shown that growth, survival, and spawning are impacted by physical (e.g. SST) and biological (e.g. phytoplankton) oceanographic processes (IATTC early life history work).

Oceanographic conditions may affect a variety of biological processes, including growth, survival, spawning, recruitment, and movement. Factors relating to the fishing process (e.g. availability of fish to the gear and the size of the fish caught) can also be impacted by oceanographic processes. The fishing related processes may be due to the behavior of the fish (e.g. a shallow thermocline keeps the fish at the surface where they are more vulnerable to purse seine) or the performance of the gear (strong currents shoal longline gear). Some of the oceanographic variables that have been hypothesized to influence population and fishing processes include SST, vertical distribution of temperature, wind, currents, phytoplankton. There have been numerous published relationships between fish population dynamics processes and oceanographic data (see the reviews in Tomczak 1977; Sund et al. 1981; Keyl and Wolff 2008). A majority of these relationships relate to water temperature (Santos 2000). However, re-evaluation of published correlations between recruitment and environmental variables with new data has showed that these correlations do not hold up over time with the exception that correlations using stocks at the limit of a species geographical range tended to remained statistically significant (Myers 1998; Myers et al., 1995). In addition, oceanographic data is often correlated making the determination of causative factors difficult (Parsons 1996) and there is the potential of multivariate climate indices for forcing ecosystem states (Keyl and Wolff 2008). The failure of environmental relationships over the long term has discouraged the use of environmentally based management (Parsons 1996).

Several approaches have been used to determine the relationship between population or fishing processes and oceanographic processes: a) manipulative laboratory experiments; b) correlations over time (e.g. years) using historical data aggregated over large areas, c) correlations over time (e.g. years)

using aggregated data from a restricted area, d) small spatial scale detailed studies, and e) correlations across space. Correlations using data aggregated by year and over large areas are most commonly used in assessment of fish stocks because they correspond to the management temporal and spatial units. These approaches generally take an annual estimate of the population process (e.g. recruitment) and correlate it with an annual estimate of a broad measure of the oceanographic conditions (e.g. average SST). Correlations with data from a restricted area are more typical of ecological experimental studies and require extrapolation outside the range of the data to the larger spatial scale to be useful in stock assessments (Walters and Collie 1988). Correlations with oceanographic variables over space are limited to processes that can easily be associated with space. For example, fine scale spatial correlations between growth and oceanographic factors for sessile invertebrates. The advantage of these spatial studies is that they do not need a long time series of data, but a single snapshot, and therefore can be done in a short period of time. Some studies look at correlations with oceanographic factors over both space and time, with space usually being at an intermediate scale (e.g. salmon stocks from different streams).

In fisheries stock assessment, recruitment is the process that is most commonly correlated with oceanographic processes for three reasons: a) recruitment is the process that varies the most; b) annual relative recruitment strength is one of the most precise and least biased quantities estimated from stock assessment models, and c) can be used for projections and management. Recruitment is typically defined as (or effectively measures) the number of individuals in a single cohort at the time when that cohort becomes vulnerable to the fishery. Several population processes affect recruitment from the number of eggs produced through survival of the different life stages up until entering the fishery. Due to the fragility of eggs and larvae it is not unexpected that recruitment can be highly influenced by oceanographic processes. Currents move eggs and larvae in or out of favorable habitat (e.g. Wilderbuer et al 2002) and move the necessary food towards or away from the individuals. Changes in temperature may increase or decrease growth rates extending or reducing the time that an individual is vulnerable to a predator. Estimates of time-varying recruitment are a standard output of most contemporary stock assessment models based on size- or age-composition data. For some species, there are direct counts of recruits (e.g. salmon) or surveys that monitor the recruits. In rare cases, there may be information about the abundance of different life stages so the influence of oceanographic processes can be attributed to different life stages (Koster et al. 2003; Maunder and Deriso 2011). Oceanographic conditions have been found to explain a majority of the recruitment variability for some stocks (e.g. Borja et al. 1998).

Recruitment is also hypothesized to depend on the parental stock size. In low fecund species (e.g. marine mammals) recruitment clearly depends on the number of adults, and for these species oceanographic processes are typically less important (the offspring are often large and receive substantial parental care). Fish tend to be highly fecund and the relationship with the parental stock is less clear. There have been numerous debates, which continue, over the relative importance of fishing (through reduction in adult abundance) and the environment on recruitment (Hjort, 1914; Walters and Parma 1996; Platt et al. 2007). The stock-recruitment relationship and environment interact, and different stock-recruitment relationships may apply in different oceanographic conditions (e.g. Basson 1999, Chen 2001;). Alternatively, oceanographic processes may only be important when the abundance

is low (e.g. Brander 2005). Environmental conditions could impact density independent or density dependent (e.g. modify the habitat and thus the carrying capacity) survival. A complicating factor is that an auto-correlated environmental effect can provide the illusion of stock-size driving recruitment, whereas recruitment does affect stock size (e.g. Yellowfin tuna in the EPO ref).

Numerous methods have been used to correlate recruitment with oceanographic covariates (e.g. GLM, GAM (Jacobson and MacCall 1995), neural networks (Chen and Whare 1999), fuzzy logic (Chen 2001)). In many cases the environmental effect is coupled with a stock-recruitment relationship. Use of the Ricker stock-recruitment model with covariates has been popular because it can be converted into log-linear multiple regression model (Hilborn and Walters 1992). However, modern nonlinear estimation methods have made this unnecessary (Fournier et al. 2011) and the most appropriate stock-recruitment model should be used rather than using a convenient computational form.

All the standard criticisms of correlating time series are relevant to correlating oceanographic data with population processes. The more oceanographic time series that are tested the more likely you will find a significant relationship just by chance. This is particularly true if the both the population process and the oceanographic processes are auto-correlated (Walters and Collie 1988). Drinkwater and Myers (1987) found that after reanalysis of correlations between environmental variables and catches of several Gulf of St. Lawrence and Gulf of Maine fishes, which took account for the loss of degrees of freedom due to the high autocorrelation of the data, none remained significant. Francis paper. Conventional approaches to avoiding spurious correlation and misinterpretation of results should be applied, including (i) hypothesizing an a priori set of conceptual mechanistic models based on oceanographic data that make sense biologically, (ii) explaining the extent of the search for correlations not explicitly included in the analysis, (iii) using data reduction techniques (e.g. principal component analysis) to combine multiple, often correlated, variables into fewer and potentially more informative indices, and (iv) using a parsimonious model that explains a high proportion of the variability in the data (Guisan et al. 2002; Haltuch and Punt 2011). Testing one covariate at a time may be misleading because covariates may only be significant in combination (Maunder and Deriso 2011).

One area that has had particular attention is the Cushing-Hjort match/mismatch hypothesis (Platt et al. 2007). This hypothesis suggests that strong recruitment occurs when food is available at the right place and time so that larvae can survive. In particular, phytoplankton blooms matched to the occurrence of larvae leads to higher recruitment (Platt et al. 2007). Platt et al. (2003) found that anomalies in plankton bloom timing accounted for 95% of the variation in haddock recruitment and suggested that early blooms were beneficial for species with protracted spawning. Additional support for the match-mismatch hypothesis has been found using data from north Atlantic cod stocks (Mertz and Myers 1994). An alternative to the mismatch hypothesis is the member-migrant hypothesis, which is based on advective losses of eggs and larvae from the favorable habitat (Sinclair 1988).

### **Integrating oceanographic data into the stock assessment model**

Contemporary stock assessment models can directly include oceanographic time series to help inform population processes. For example, the Stock Synthesis general stock assessment program (Methot 2009), which is used to assess a wide variety of stocks in the USA, can model covariates with most

estimable parameters including both biological and fishing processes. Including the oceanographic data in the model allows all the data in the model to inform the correlation, automatically accommodates the uncertainty about the population processes, and allows the oceanographic data to inform the model for years in which there is little other information (Maunder and Walters 2003).

Statistically rigorous methods to include covariates into stock assessment models have been well developed (Maunder and Watters 2003; Deriso et al. 2008). The covariates can be used to provide information on both population (recruitment, growth, natural mortality) and fishing processes (e.g. catchability, selectivity). The correct modeling of both sampling and process variability (error) is important for selecting covariates to avoid bias in selecting covariates. Likelihood ratio and AIC-based tests are biased towards incorrectly accepting covariates if the unexplained process error is not modeled (Maunder and Watters 2003). Other tests, such as randomization tests, should be used if it is not possible to model the additional process variability (Maunder and Watters 2003; e.g., Deriso et al. 2008). Incorrect sampling distribution assumptions (e.g., the assumed value for the standard deviation of the likelihood function) can influence the covariate selection process, and the weighting given to each data set can change which covariates are chosen (Deriso et al. 2007). In situations where data-based estimates of the variance or related parameters (e.g. sample size) are not available, estimating the variance as a model parameter or using concentrated likelihoods is appropriate (Deriso et al. 2007). Missing covariate data need to be dealt with appropriately, such as by using the methods described in Gimenez et al. (2009) and Maunder and Deriso (2010). Schirripa et al. (2009) investigated two ways of including environmental variability into stock assessment models a) structural and b) as data. The data method allows for observation error and missing data in the environmental time series. Neither method performed better than the other and because they handled missing data differently the best approach is dictated by the missing data.

Oceanographic data is most commonly integrated into stock assessment models to drive recruitment (e.g. Maunder and Watters 2003). Many of the comments made in the previous section are valid when integrating oceanographic data into the stock assessment model. For example, integrating oceanographic data with decadal-scale variability into the stock assessment model via the stock-recruitment relationship can cause high type I error (incorrectly rejecting the null hypothesis of no environmental relationship) when fishing related declines coincide with directional oceanographic change (Haltuch and Punt 2011). Oceanographic data has been integrated into stock assessment models to describe movement among sub-populations in spatially explicit models. Dorn (1995) integrated the relationship between water temperature and spatial distribution of Pacific whiting into a stock assessment model to estimate migration curves. Su et al. (2011) integrated relative densities inferred from habitat preferences based on oceanographic variables to estimated movement of blue marlin.

## Harvest strategies

Fish population variability caused by oceanographic processes makes harvest strategies more difficult to implement. To improve the performance of harvest strategies managers can either attempt to explain

this variability or develop strategies that are robust to the variability (Basson 1999). Oceanographic data can be used to either a) improve predictions of abundance which are used in harvest rules and/or b) adjust the parameters of the harvest rule (e.g. the harvest rate or escapement goal is a function of the oceanographic data).

Despite the large number of correlations between population processes and oceanographic covariates (Tomczak 1977; Sund et al. 1981; Keyl and Wolff 2008), and proposals to use environmental based harvest rules (e.g. [Hurtado-Ferro et al. 2010](#); Zhang and Lee 2001), few management strategies directly incorporate the correlation (Sharp 1995). There may be more examples, but still few, in which the estimates of abundance used in the harvest rules are based on information from the oceanographic data (e.g. predictions of recruitment). Myers (1998) reviewed the use of environment–recruitment relationships over a 20 year period and found that very few stocks with a previously identified relationship were currently being used in stock assessments or management strategies. One example is the harvest rule for sardine off the west coast of North America that has a trigger based on SST, although the trigger has never been activated (see PFMC in Punt 2011). The management rule for Pacific sardine is based on the correlation between recruitment and SST developed by Jacobson and MacCall (1995).

Predicting population processes should, in theory, improve the ability to manage a fish stock. For example, knowing the amount of recruits entering the fishery each year based on a correlation with an oceanographic covariate will improve the quality of estimates of total allowable catch based on fishing mortality control rules. The usefulness of recruitment predictions from oceanographic data will depend on 1) what proportion of the recruited population is comprised by the recruiting cohort, 2) what percentage of the variation in recruitment is explained, 3) how many years in advance recruitment can be predicted, and 4) at what age fish enter the fishery. The number of years in advance that recruitment can be predicted is dependent on which life-stage the covariate correlates with and on the age at which the fish recruit to the fishery. In some cases, the oceanographic process that correlates with recruitment can be predicted in the future increasing the number of years in which recruitment can be predicted. Predictions about future oceanographic conditions (e.g. climate change) are required to improve management in the medium and long term (Basson 1999). However, predicting the oceanographic process adds additional error to the relationship and will reduce the proportion of variation explained.

Oceanographic conditions can cause variability in population processes and the robustness to this variability differs among management schemes. Several simulation studies have been conducted to evaluate which management schemes are robust to the variability. There are three traditional harvest rules used to manage fish populations: a) constant catch; b) constant harvest rate; and c) constant escapement. In cases where oceanographic variation drives population abundance, taking a constant amount of fish each year is either risky because in years of the low abundance the catch might be too high and collapse the stock, or the constant catch has to be set conservatively low with considerable loss in yield in years of high abundance. Constant harvest rate and constant escapement management strategies are feed-back strategies allowing the harvesting of more fish when the population abundance is high. Constant catch strategies have lower variation in annual catch, while constant escapement strategies have higher variability in catch, which may be an important consideration for the fishing

industry. Constant exploitation rate (catch = rate times abundance) and constant escapement harvest strategies (catch all of the fish above a certain level so there is always the same number of fish in the population) require good estimates of abundance otherwise the catch might still be set too high (or too low). Constant exploitation rate harvest strategies could be implemented through constant effort, which reduces the need to have accurate annual abundance estimates. However, changes in the efficiency of fishing vessels may reduce the effectiveness of constant effort management strategies (Walters and Parma 1996). Catchability may also change with the oceanographic conditions so effort based rules might need to be link to the oceanography. Hybrid strategies that only take a fraction of the stock above the escapement goal have also been abdicated. In addition to accurate estimates of abundance (for constant escapement and constant harvest rate strategies), these strategies also need accurate population dynamic models to determine the optimal parameters of the harvest rule (i.e. the constant catch level, harvest rate, or escapement goal).

Walters and Parma (1996) showed constant harvest strategies perform within 15% of the theoretical optimum for a wide range of populations. Constant escapement strategies are optimal when recruitment is stationary and uncorrelated (Walters and Parma 1996), but require time varying escapements that allow a build-up of the spawning biomass in anticipation of favorable conditions in the presence of nonstationary recruitment (Parma 1990). Parma (1990) showed that with cyclic recruitment, constant harvest rate strategies also inherently allow a buildup of spawning biomass during favorable periods. Therefore, strongly auto correlated oceanographic forcing of recruitment would improve the performance of constant harvest rate strategies relative to constant escapement strategies (Walters and Parma 1996). Several studies have shown that constant harvest rate strategies do not perform much worse than harvest strategies than know the oceanographic conditions (Walters and Parma 1996, Punt 2011, Basson 1999; A'mar et al. 2009), which implies that it may be more cost effective to invest in developing constant harvest strategies than to invest in detecting oceanographic relationships and oceanographic prediction (Walters and Parma 1996). Harvest strategies with oceanographic correlations might perform best for single cohort short lived species such as squid and salmon. Agnew et al. (2002) proposed a method for using predictive relationships with the environment for managing squid stocks. Their method varies effort based on the environmental covariates and reduces risk of not meeting conservation targets while increasing yield. However, given the poor track record of correlations holding up over time, in-season monitoring may be a better choice (Walters and Collie 1988).

Harvest strategy performance will depend on whether recruitment variation is density dependent (variation in carrying capacity) or density independent and environmental effects on carrying capacity appear to dominate harvest strategy performance (Walters and Parma 1996). Most research has focused on the performance of harvest strategies in the presence of variation in recruitment, however the optimal harvest strategies could also depend on how oceanographic processes influence other factors like adult growth or adult natural mortality (King and McFarlane 2006).

Biological reference points (e.g.  $B_{msy}$ ,  $F_{msy}$ ) that are used in harvest rules and as general indicators of the stock status can be influenced by oceanographic conditions. Including oceanographic data in stock assessments may improve the estimates of biological reference points (Basson 1999; Haltuch and Punt 2011). Biomass based biological reference points can be particularly impacted by regime shifts since

they are highly dependent on the average recruitment. However, there are few examples of explicitly using regimes in management of populations (King and McFarlane 2006). Dynamic biological reference points (e.g. dBmsy and dB0), which take the historic time series of recruitment into consideration, might be more appropriate when oceanographic processes drive recruitment or in the presence of regime shifts. These are calculated by projecting the population over the historic period using the estimated historic time series of recruitment (adjusted for the stock-recruitment relationship if necessary) and applying the appropriate fishing mortality (Fmsy for dBmsy and F=0 for dB0). The calculations are similar to those used in fishery impact analysis (see Wang et al. 2009).

Several authors have advocated regime-specific harvest rates showing that they are optimal (Spencer 1997; Peterman Pyper and Grout 2000; MacCall 2002) and that constant harvest rate strategies were more appropriate for long-lived species (MacCall 2002). These strategies don't require prediction of regime shifts, although the necessary response time is dependent on the life-history of the species. Climate change may also impact the management required to sustain fish populations. Hollowed et al. (2009) outlined a framework for forecasting the impacts of climate change on fish stocks. Hare et al. (2010) used temperature forecasts from general circulation models to model Atlantic croaker abundance and spatial distribution. These approaches could be used to develop management strategies to cope with climate change. In the presence of long-term slow changes the best short-term policy may be to assume that the current conditions apply. Oceanographic driven trends in recruitment will also impact the performance of rebuilding plans (Punt 2011).

## Spatial management

Spatial closures have been historically used to protect bycatch species and specific vulnerable components of the population (e.g. juveniles). However, recently spatial closures (protected areas) have been promoted as a general fisheries management tool to manage target populations. To date spatial closures have generally been static (Dunn et al. 2011). They are useful in protecting sedentary species or specific habitats (e.g. spawning areas), but can be ineffective for highly mobile species. Oceanographic conditions can be used to define a species' preferred habitat and guide the creation of static spatial closures. In conjunction with maps of oceanographic climatologies, physiological limits or preferences offer clear choices for static fishery closures based on persistent oceanographic features (Dunn et al. 2011). Habitat preferences of commercial and bycatch species based on oceanography have been developed (e.g. Redfern et al. 2006; other refs), but have rarely been incorporated into active resource management planning (Dunn et al. 2011).

The ocean is a dynamic environment and the spatial distribution of the preferred habitat may change over time. Therefore, if there are no predictable spatial or temporal patterns, the spatial constraints of the closed area may need to be dynamic and based on the changes in oceanographic conditions (e.g. see the Pacific Islands Fishery Science Center Turtlewatch tool, <http://www.pifsc.noaa.gov/eod/turtlewatch.php>). Unfortunately, enforcement of spatial closures is problematic if they are dynamic so there is a tradeoff between the frequency of changes in the closed area to optimize the benefits and the

ability to enforce the closure. The obvious choice is to limit the number of changes in the closure. Although, vessel management systems that track the location of vessels and modern communication tools can facilitate short notice closures and assist enforcement (Dunn et al. 2011). An alternative is not implement a closure, but combine vessel catch limits with advice about ways to avoid catching the species. For example, real-time maps of the spatial distribution of a species based on predictions using oceanographic data can be provided to the fishing industry that they can use to avoid areas where that species is located. Oceanographic conditions could also be used to trigger a spatial closure (Dunn et al. 2011).

A successful dynamic spatial closure has been implemented in Australia's eastern tuna and billfish fishery (Hobday and Hartmann 2006; Hobday et al. 2009). The closure is designed to reduce the bycatch of Bluefin tuna in the tropical tuna longline fishery. The habitat preference of Bluefin tuna is obtained from pop-up satellite archival tags and oceanographic data is used to define preferred areas that are closed. The methods used to define the closure have been refined over time and now use oceanographic models to predict vertical habitat. Using a predictive ocean atmosphere model STB distribution is forecast at lead times of up to 4 months to better inform operational decisions (Hobday et al. 2011). The management approach is based on similar concepts as used to develop the habitat based CPUE standardization presented above and will therefore encounter some of the same issues.

Check these: Sea surface temperature is the basis for a voluntary closure in both the United States (Howell et al. 2008) (e.g. turtles off North Carolina see <http://www.epa.gov/fedrgstr/EPAIMPACT/2002/March/Day-21/i6772.htm> and Coles and Musick, 2000),

## Multi-species and ecosystem models

Unlike single species models, ecosystem models incorporate the interaction of species, and can depict top-down changes in trophic structure, trophic cascades, and feedbacks through the food web. External drivers such as fishing and climate modify the internal food-web dynamics of exploited ecosystems. Ecosystem models can be used to ask if top-down effects of fishing might be detectable over background variability imparted by the environment and to provide insight into the relative roles of fishing and the environment in regulating population change (Watters et al. 2003; Lindegren et al. 2009). Environmental perturbations influence commercially targeted species from the bottom-up by means of indirect physical effects on primary production and direct effects on reproductive success and growth.

Ecosystem models can be configured to be driven by time series of primary production (Watters et al. 2003). Primary production is highly influenced by oceanographic conditions. For example, primary production and phytoplankton biomass are reduced during warm El Niño periods and increase during cold La Niña periods in the eastern Pacific Ocean (EPO) (Barber and Chavez 1983, Fiedler et al. 1992, Barber et al. 1996). Moreover, the growth rates and reproductive success of various birds, mammals, and fishes are reduced during El Niño events (Barber and Chavez 1983). Watters et al. (2003) used time series of sea-surface temperature anomalies to force the biomass of large phytoplankton (diatoms) and predator recruitment in an ecosystem model for the pelagic EPO. The time series were from two sources

representing two scales of environmental variation, ENSO and global warming. Model simulations indicated that bottom-up effects may propagate through the entire food web, and time lags are an important component of the response. Top-down effects of fishing were detectable over the variability induced by the environment for the less productive predators or those that were heavily fished, but not for most forage components. Response to a long-term warming trend depends on the level of fishing.

Ecosystem models require a lot of information for their construction due to the inclusion of a variety of species. Unfortunately, the required information is often lacking for some of the species, and assumptions based on information for related species are required. It is not clear how useful ecosystem models are for fisheries management, but their development will help in the understanding of oceanographic processes on the ecosystem and how they interact with fishing. Ecosystem models may be useful in developing hypotheses about the impact of oceanography and climate change on marine ecosystems.

There are several multi-species stock assessment models that incorporate a limited number of species interactions and allow for the inclusion of oceanographic processes. (Bogstad et al., 1997; Stefansson and Pálsson, 1998; Tjelmeland and Bogstad, 1998; Begley and Howell, 2004; Stock et al 2011). These models can simultaneously evaluate the effects of fishing, species interactions, and oceanographic processes. Lindegren et al. (2009) used a multispecies model to develop an ecosystem based management approach for the Baltic cod stock. They demonstrated that a harvest rule that changed with the oceanographic conditions could have prevented the cod stock collapse. The development of the harvest rule took into consideration of how the oceanographic processes interacted with the trophic interactions.

### **Mechanistic and individual based models**

An alternative approach to standard stock assessment models is to develop more detailed models based on mechanistic relationships between different life stages and their ocean environment. The methods generally rely on parameters estimated from detailed experiments or assumptions rather than broad scale relationships or parameters estimated by fitting the model to data. However, some applications have taken advantage of efficient parameter estimation techniques (Fournier et al. 2011) and advances in computing power to estimate model parameters by fitting to data (Senina et al., 2008). Fine scale spatial structure is often a major component of these models that use oceanographic processes to advect and diffuse the individuals or their prey (Miller 2007). Development of the first individual-level coupled physical-biological models (ICPBM) of fish early life history occurred in the late 1980s (Bartsch 1988; Bartsch et al. 1989) and have contributed significantly to the understanding of recruitment processes in marine fish populations (Miller 2007).

A spatial environmental population model (SEAPODYM) has been developed to model tuna stocks in the Pacific Ocean (Bertignac et al., 1998; Lehodey et al., 1998; Lehodey, 2001). The model is a two-dimensional coupled physical–biological interaction model at the ocean basin scale, and contains

environmental and spatial components used to constrain the movement and the recruitment of tuna. The model combines a forage (prey) production model with an age-structured population model of the fishery target (tuna predator) species. All the spatial dynamics are described with an advection–diffusion equation. Oceanographic Input data sets for the model are sea surface temperature (SST), oceanic currents and primary production that can be predicted data from coupled physical–biogeochemical models, as well as satellite-derived data distributions. Simulations were able to reproduce the observed ENSO-related spatio-temporal changes in the distribution of skipjack (*Katsuwonus pelamis*) population (Lehodey, 2001; Lehodey et al., 1997). Recent improvements include rigorous parameter optimization using fisheries data (size composition and abundance indices), which are based on methods used for contemporary stock assessment models (Senina et al., 2008).

### Improving surveys

Incorporating oceanographic information into surveys for fish stocks can sometimes be beneficial in terms of improving the precision of estimates of abundance and improving survey efficiency by guiding allocation of effort. Abundance can vary spatially (and possibly temporally) due to spatio-temporal variability in habitat. Historical oceanographic and abundance survey data may be useful in survey planning (e.g., pre-stratification of the survey region into subareas with similar species densities). Oceanographic data collected real-time during the survey may be useful for implementation of adaptive cluster sampling designs. Real-time collection of oceanographic data also may be useful for post-stratification of survey data (e.g., Thompson, 1992), for example, based on GLM or GAM analysis of the relationship between CPUE and environmental descriptors (see the section on CPUE standardization above). For surveys based on line transect methods (e.g., Buckland *et al.* 1993), the probability of detection can be modeled post-survey as a function of environmental covariates (e.g., Marques and Buckland, 2003; Hedley and Buckland, 2004).

The approach taken for pre-stratification of the survey region depends on data availability and knowledge of the mechanisms responsible for spatio-temporal structure in species density. Following the general principles for optimal allocation of samples in stratified sampling designs (e.g., Thompson 1992), it is desirable to collect more samples in strata where abundance is more variable. Often variability in abundance increases with mean abundance. If it is known from previous surveys that different levels of abundance are associated with different oceanographic conditions, it may be useful to subdivide the survey region into subareas based on known oceanographic conditions, allocating more effort to subareas with conditions associated with greater species density. For species for which there is a strong habitat preference, historical oceanographic and survey data could also be used to design surveys which allocate most survey effort to the oceanographic conditions the species inhabits (e.g., Zwolinski *et al.* 2011). However, in any ecosystem, environmental variability that is not predictable will make *a priori* definition of strata with suitable habitat problematic (Defeo and Rueda 2002). If previous survey data are not available for the species of interest, but are available for other species with similar environmental ‘preferences,’ subareas could be determined from analysis of these data. This may be particularly beneficial when designing surveys for rare species based on data of more common species

with similar distributions (Edwards *et al.* 2005). This same type of approach might be useful if data were available for the species of interest, but from a different region, as long as oceanographic conditions and underlying processes were similar.

Adaptive sampling strategies take advantage of real-time information on species density to increase sampling intensity in subareas where individuals are more abundant, and have been shown to be useful for sampling rare and clustered species. There are several types of adaptive sampling strategies. Adaptive cluster sampling (e.g., Lo *et al.* 1997; Thompson 2002; Thompson 2004 and references therein) generally involves an initial sampling phase where a fixed number of units are selected at random to be sampled (“primary” units). If, during the survey, it is found that the species density exceeds a pre-specified threshold in any of these primary units, then further sampling of neighboring primary units is done until no adjacent primary units are found to exceed the threshold. Simulations suggest that adaptive cluster sampling may perform better than conventional sampling methods for bluefin tuna in the Atlantic (Newlands *et al.* 2007). However, one problem with adaptive cluster sampling designs is that the final sample size is not known in advance, making survey planning difficult. Adaptive two-stage and sequential sampling designs (e.g., Francis 1984; Brown 1999; Manly, 2004; Thompson 2004 and references therein; Smith and Lundy 2006; Brown *et al.* 2008; Smith *et al.* 2011) are adaptive strategies that can be more practical. In these types of designs, information collected during the first stage of sampling is still used to allocate additional effort in the second phase of sampling, but the total effort allocation for the survey can be fixed in advance. As a simple example of an adaptive two-stage design, a fixed amount of effort is allocated to each of several strata. Data collected on species density from this first stage are then used to allocate the remaining effort to strata, for example, allocating a fixed amount of additional effort to strata with density or coefficients of variation of density greater than a pre-specified threshold. In a modification to this type of strategy, Lo *et al.* (2001) sampled along a predetermined series of transects and increased sampling intensity when density exceeded a predetermined threshold but did not add additional transects.

Extending adaptive sampling designs to incorporate oceanographic data might be done in several ways. Sampling (e.g. bottom trawls or plankton net tows) along a transect leg might only be done when the oceanographic conditions are within predefined limits. For example, Richards *et al.* (1989) used real-time satellite data to select ichthyoplankton survey transect locations conducted in the Gulf of Mexico for sampling bluefin tuna (*Thunnus thynnus*) larvae. Following the general approach of Lo *et al.* (2001), sampling frequency (intensity) might be based on the oceanographic conditions instead of on species density. Adaptive sampling designs have recently been proposed that make use of information on an auxiliary variable to determine the level of second stage sampling (Panahbehagh *et al.* 2011). The types of data that would be required for these types of adaptive sampling designs are the same types of habitat preference and oceanographic data used for CPUE standardization and spatial management as presented above, except that the data are required in real-time. Simulations of adaptive sampling design for fish stocks using auxiliary oceanographic data and on the appropriate estimators for such sampling designs may prove useful.

## Discussion and Future

Despite the criticisms that fisheries stock assessment and management have neglected oceanographic processes (e.g. Parsons 1996), there has been a significant amount of research devoted to improving fishery stock assessment and management by incorporating oceanographic processes. The lack of application in the real world is a consequence of the inability to find correlations between population processes and oceanographic data that persist over time. Recruitment has been most commonly correlated with oceanographic processes (usually some measure of water temperature) because it is the most variable processes and can often be reliably estimated. Unfortunately, recruitment, measured when the fish enter the fishery, is a consequence of many different survival processes at different life stages (Walters and Collie 1988), which may be driven by different oceanographic processes. Therefore, it is not surprising that there has been a lack of success using oceanographic processes to predict enough of the variability in recruitment to benefit fisheries stock assessment and management. The lack of success has led to research into harvest strategies that are robust to the variability caused by oceanographic processes. It has prompted the argument that it is better to focus on developing monitoring programs than investigating correlations between recruitment and oceanographic conditions (Walters and Parma 1996).

Oceanographic conditions affect more directly the spatial distribution of highly mobile fish, due to their physiological limits or preferences. Therefore, development of correlations between the spatial distribution of a stock and oceanographic processes is much more promising. The use of these correlations to avoid bycatch species through, for example, dynamic spatial closures is where research should be directed. Similar arguments could be made for the definition of stock boundaries used in management or stock assessment, which could be dynamic and based on the oceanography. The new synoptic oceanographic data collected by remote sensing has greatly expanded the scope of research questions that can be addressed compared with what is possible using ships alone (Platt et al. 2007). The much broader range of temporal and spatial scales means that research questions can now be addressed at the relevant scales (Platt et al. 2007). However, it is likely that this information will be most beneficial for evaluating the influence of oceanography on the spatial distribution of a stock.

There has been a trend towards evaluating the impact of climate change on marine ecosystems and fisheries. However, uncertainty in climate model projections, the uncertainty in the mechanisms underlying the response of populations to climate, the uncertainty in trophic interactions, and extrapolation outside current oceanographic conditions make any predictions highly uncertain (Stock et al. 2011). Therefore, management strategies should be developed to be robust to climate change and its uncertainty.

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