Exploring Spatial Heterogeneity of CPUE Year Trend and Nonstationarity in Fisheries Stock Assessment, an Example Based on Atlantic Weakfish (Cynoscion Regalis)

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Abstract

Quantitative population dynamics modeling is needed to evaluate the stock status and fisheries management plans to provide robust model and management strategies. Atlantic Weakfish (Cynoscion regalis), one important commercial and recreational fish species along the west coast of Atlantic Ocean that was found to be declining in recent years, was selected as an example species. My study aimed to explore the possible spatial heterogeneity of CPUE (catch per unit effort) year trend based on three fishery-independent surveys and explore the influence of nonstationary natural mortality on the fisheries management through a MSE (Management Strategy Evaluation) algorithm based on the Weakfish stock assessment results. Five models for catch rate standardization were constructed based on the NEAMAP (NorthEast Area Monitoring and Assessment Program) survey data and the 'best' two models were selected based on the ability to capture nonlinearity and spatial autocorrelation. The selected models were then used to fit the other two survey data to compare the CPUE year trend of Weakfish. Obvious differences in distribution pattern of Weakfish along latitude and longitude were detected from these three surveys as well as the CPUE year trend. To test the influence of the model selection on the MSE, five stock-recruitment models and two forms of statistical catch-at-age models were used to evaluate the fishery management strategies. The current biomass-based reference point tends to be high if the true population dynamics have nonstationary natural mortality. A flexible biomass based reference point to match the nonstationary process is recommended for future fisheries management.

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List of Abbreviations

CPUE: Catch per Unit Effort

MSE: Management Strategies Evaluation

SCA: Statistical Catch-at-age Model

NEAMAP: Northeast Area Monitoring and Assessment Program

CHESMMAP: Chesapeake Bay Multispecies monitoring and Assessment Program

NMFS: National Marine Fisheries Service

GLM: Generalized Linear Model

GAM: Generalized Additive Model

SAR: Simultaneous Autoregressive Model

Chapter 1
General Introduction

1.1 Current approaches to fisheries management

The decline and collapse of fisheries have been frequently observed, with causes being attributed to poor management of natural resources (Myers and Worm, 2003), overcapitalization, scientific uncertainty, and intricate ecosystem structure (Ludwig et al., 1993). According to the assessment report from Food and Agriculture Organization (FAO) in 2009, approximately 25% to 30% of fish stocks are being overfished (FAO, 2009). The process of fisheries management is always complex since there are interactions among the stakeholders, natural population dynamics, and uncertainties (Walters and Hilborn, 1976).

Novel approaches to fisheries management such as marine protected areas (MPAs), catch shares (i.e., Individual Transferable Quotas), conservative biological targets, and ecosystem-based incentives (Weeks and Berkeley. 2000; Pauly et al., 2002; Latour et al., 2003; Costello et al., 2008) have been prompted due to continued decline of marine fish stocks. Traditionally, management of natural resources used to ignore the dynamics and uncertainties in natural systems, which turned out to be a failure. Adaptive harvest management (AHM) is successfully used to solve some problems it, however, seems to be effective only if the system is fairly simple or relatively stable. When it comes to multiple stakeholders and uncertainties, AHM usually does not work well in working out an optimal solution (Bunnufeld, 2011).

1.2 Catch rate standardization

Catch rate standardization is essential in fisheries to allow comparisons of catch rates over time or over different areas. In fisheries, commercial catch rates are often standardized for use as an index of relative abundance, particularly in fisheries where a regular resource survey has not been feasible (Hilborn and Walters, 1992; Maunder and Punt, 2004). In order to be helpful and comparable as an index of relative abundance, raw catch rate must be standardized for changes or variations in catchability, otherwise changes in catch rate that are indicting variable catchability may be attributed to changes in abundance. However, standardization can be very problematic, and standardized results are not always proportional to real abundance (Harley et al., 2001; Maunder et al., 2006). The lack of proportionality can happen especially when inappropriate methods (i.e., statistical models) are used to construct the standardized index of relative abundance; for example, methods that fail to account for spatial variation and nonlinearity in fishing effort (Walters, 2003; Campbell, 2004). Another cause may be inadequate standardization for variations in catchability, including changes in fleet composition and effort creep within vessels.

A commonly applied method of standardizing catch rates is to fit a regression model. Typically, a linear regression is fitted, with suitable choices of distributional form and treatment of effort with zero catches (Maunder and Punt, 2004). The dependent variable is catch rate (i.e., weight or count per unit effort), and explanatory variables represent environmental factors (water temperature and depth), effort, vessels, and gear (Kimura, 1981; Allen and Punsly, 1984; Maunder and Punt, 2004). In a simple model, the year effects corresponding to the indices of relative abundance have remained constant over the years (Allen and Punsly, 1984; Hilborn and Walters, 1992; Walters, 2003; Campbell, 2004; Maunder and Punt, 2004).

1.3 Management strategy evaluation (MSE)

MSE is a simulation-based process by comparing a series of alternative management strategies and assessing the consequence of each strategy under several management objectives in a virtual world. MSE also includes the process of designing and testing management procedures (MPs), which are reasonable for the objective to meet (Figure 1.1). Instead of achieving an optimal strategy or decision, its goal is to provide fisheries managers information to make feasible policies which are robust to uncertainties and errors in natural system. The impact of uncertainties and errors in fisheries stock assessment has resulted in the development of biologically risk-diminishing tasks that account for scientific uncertainties about fish stock status and alternative management approaches (Jiao et al., 2005; Shertzer et al., 2008). The advantages of MSE over other kinds of approaches are that it enables the stakeholder to participate in developing management plans. Besides, MSE allows researchers and managers to test the involvement of uncertainties and errors when implementing various management actions.

The MSE approach was first introduced by the Scientific Committee of the International Whaling Commission (IWC) in the late 1980s (Punt and Donovan 2007). MSE has been applied to fisheries since then and has achieved great success in the fisheries management, as well as having helped to rebuild fisheries that have declined or been endangered. MSE is mainly applied in single-species fisheries, but it can also be conducted in multispecies fishery (Smith and Sainsbury, 1999).

For the purposes of MSE, a management strategy is the combination of the procedures related to how a resource is monitored, how its status relative to target and limit reference points is determined (the "estimation model"), and how the results of the estimation model are used to determine management actions (the "decision" or "catch control" rule). A management strategy can be complex, involving a stock assessment model coupled with a decision rule (such as that adopted for the management of commercial whaling by the International Whaling Commission; e.g., Cooke 1999, International Whaling Commission 1999), or it can be very simple, such as a decision rule that uses empirical data (e.g., those adopted for anchovy and sardine off South Africa, De Oliveira et al., 1998). In fact, any quantitative method that determines management actions, such as limits on fishing mortality or acceptable biological catch (ABC), gear restrictions, or spatial or temporal limitations, could be evaluated using MSE. The focus of MSE has been on management of single-species fisheries, but there is no reason that management strategies designed primarily to achieve ecosystem objectives could not be evaluated using the MSE approach (Sainsbury et al., 2000, Butterworth and Punt 2003).

In the first step of MSE, an operating model is used. In most MSE processes in fisheries, the operating model is age-structured, and estimates recruitment to spawning biomass individually or dependently. This model is used to estimate the stock-recruitment relationship parameters, the fishing mortality for every year, and the fishery selectivity for each age, and the catchability coefficients for each survey.

After an operating model is fitted to fishery and survey data by a specific method (Bayesian methods for example (A'mar, 2008)) to get the optimal estimates of parameter values, simulations are done to represent the real problem in management of a fish species. The simulated stock is projected for years based on a simulated management strategy or control role and generates the survey and fishery data needed by the assessment model in the following year.

The assessment model is created for the input for the decision rules which determines the allowable harvest and estimates fishing mortality and spawning biomass. The estimations of fishing mortality, spawning biomass, as well as allowable catch are tested by the estimation performance measures, which are able to assess the information provided by assessment model for determining the harvest in the following year. The management performance measures are often selected to evaluate the management system to maintain the fish stock at a sustainable level and prevent the stock from being overfished or reach other management objectives.

The last step of MSE is risk assessment. Risk assessment is the process that evaluates possible outcomes or consequences and estimates their probability of occurrence. It is an efficient method to screen out low-risk activities and focus on those that have an adverse impact on population sustainability. The results of MSE are performance measures that quantify the extent to which a management strategy is able to satisfy the (often conflicting) management goals and objectives (Kell et al., 2006). In addition, the results of MSE can be used to determine how well estimation models are able to estimate quantities (such as current biomass) that are of management interest. MSE has been used to evaluate current and alternative management strategies for many fisheries worldwide, including those for South African sardine and anchovy (De Oliveira et al., 1998, De Oliveira and Butterworth 2004), prawns off northern Australia (Dichmont et al., 2006), species in Australia's South East multispecies fishery (Punt et al., 2002), krill off Antarctica (Constable 2005), and flatfish in the Northeast Atlantic (Kell et al., 2005).

Noticing the decline of Weakfish resources, fisheries researchers from the U.S. Atlantic States Marine Fisheries Commission (ASMFC) along with other councils and fishery institutions, have developed a series of amendments and addendums to serve for Weakfish to recover. Currently, however, Massachusetts, Connecticut, South Carolina, Georgia, and Florida maintain *de minimus* status, and are therefore exempt from certain regulatory and monitoring requirements. These amendments and addendums include habitat conservation and fish population recovery strategies, such as controlling commercial and recreational fishing mortality, and restoring age and size structure of Weakfish. Based on the available data, different hypothetical biological processes and restoration strategies will be considered in my study. Specifically, the effect of spawning stock biomass and recruitment relationship will be assessed to indicate its influence on the persistence of Weakfish.

1.4 Weakfish life history

The Weakfish here is used as an example to explore the "best" model which will be used in catch rate standardization and MSE process. Atlantic Weakfish (*Cynoscion regalis*) is a large marine fish species that is found along the western coast of the Atlantic Ocean, being one of the most abundant fish species within the Mid-Atlantic Bight (Shepherd and Grimes 1983) (Figure 1.2). Weakfish exhibits northerly, inshore migrations during the early April, entering estuaries and bays along the eastern U.S. coast to feed and spawn (Lowerre-Barbieri et al., 1995). As water temperatures cool, fish form aggregates that move offshore and more south to overwintering grounds (NEFSC 2009), which occur along the continental shelf from Chesapeake Bay to Cape Lookout, North Carolina (ASMFC 2004).

Weakfish spawns in the nearshore and estuarine areas of east coast of North America after the inshore migration in spring. The starting and length of spawning season in different areas are different along the coast. The spawning season starts in March and extends to September in North Carolina (Merriner 1976), which is earlier and longer than those to the north. From Delaware Bay to the north, the spawning season is from May to mid-July (Shepherd and Grimes 1984). Most (about 90%) weakfish matures by age 1 through out their distribution range and spawns multiple times in a season and has indeterminate fecundity (Lowerre-Barbieri et al., 1996). Spawning frequency and batch fecundity vary year from year and these two variables can both affect total egg production jointly (Nye and Targett 2008).

The diet of juvenile weakfish has been observed to vary both spatially as well as temporally in studies conducted in Delaware Bay and Chesapeake Bay (Hartman and Brandt 1995, Grecay and Targett 1996, R. Latour, Virginia Institute of Marine Science, pers.comm). Mysid shrimp was found to dominate the diet of juvenile weakfish collected in Delaware Bay in 1986, while the bay anchovy dominated the diet of juvenile weakfish collected in the Chesapeake Bay in the early 1990s (Grecay and Targett (1996)). Older weakfish become increasingly piscivorous with age, Atlantic menhaden or other clupeids are main food older weakfish (Merriner 1975, Hartman and Brandt 1995).

Weakfish grows rapidly in the first year, and age-1 fish usually have a wide range of sizes due to the protracted spawning season. Length becomes much less reliable as predictor of age due to an increasing overlap in lengths occurring over several age groups after age-1. And the length at age to be similar between genders with females slightly longer at age than males (Lowerre-Barbierri et al., (1995)). The historical maximum age recorded using otoliths is 17 years. The fish was collected from Delaware Bay in 1985. Historic changes in the maximum size and age have been reported with weakfish typically obtaining their maximum size and age during periods of higher landings (Lowerre-Barbieri et al., 1995). More recent growth rates have slowed to the point that mean lengths at age of adults are several centimeters shorter than they were in the early 1990s (Lowerre-Barbieri et al., 1995, Kahn 2002).

1.5 Weakfish management history

Weakfish have supported one of the most important fisheries resources along the western coast of the Atlantic Ocean since the 1800s. The landings have shifted widely since the early 1900s (Nye et al., 2008). Constant catch statistics for Weakfish can date back to the 1950s, with landings peaking in 1980 at a record of 18,000 MT. During the 1980s, landings fluctuated somewhere between 8,000 and 10,000 MT, with subsequent declines in harvest from 1989 afterwards, reaching a lowest point at 388 MT in year 2007. Connecticut, South Carolina, Georgia, and Florida maintain *de minimus* status, with every state between Massachusetts and Florida having once expressed interest in Weakfish (NESFC 2009).

Currently, the Weakfish population is listed as "depleted, overfishing not occurring" by the ASMFC, with least harvest amount being reported in recent years (ASMFC 2009). Declines in harvest were first acknowledged in year 1985 (Figure 1.3), when the ASMFC put into effect a voluntary IFMP to reduce the impact of overfishing through reducing in targeted catch and bycatch of Weakfish in shrimp trawlers (ASMFC 1985). However, none of the member states adopted every measure proposed in the IFMP, as suggested by the ASMFC (NEFSC 2009). Another attempt to prevent Weakfish stock decrease was Amendment 1, which was adopted to the IFMP in 1991 that specified the reduction amount of the harvest and bycatch by 52 and 50% respectively, in 4 years (ASMFC 1992). However, still no member state with directed fisheries for Weakfish adopted all the recommendations put forth in Amendment 1 by the ASMFC (NEFSC 2009).

The Atlantic Coastal Fisheries Cooperative Management Act of 1993 was promoted due to the resistance of Amendment 1 of member states, which mandated observance of every regulation detailed in the IFMP for Weakfish (NEFSC 2009). After the Act, the ASMFC passed Amendment 2 of the Weakfish IFMP that required a minimum total length (TL) size limit (12") and a 50% reduction in bycatch of Weakfish in shrimp trawlers, to be achieved by 1996. A 50% reduction in fishing mortality rate (F) was also approved, with a 25% reduction in fishing mortality per year during 1995 and 1996 (ASMFC 1996).

However, Weakfish spawning stock biomass and catch rate continued to decline after 1996, along with the observance of an abridged age structure. As a result, Amendment 3 was adopted by the ASMFC to reduce fishing mortality to the target level of 0.50 by year 2000, and return age structure to previous levels, and restore Weakfish to their historic range (ASMFC

1996). This was attempted through a series of management plans which included gear restrictions, bag limits, and required bycatch reduction devices (BRDs). The stock assessment for Weakfish year 2000 indicated that Amendment 3 was comparatively successful, with estimated biomass being relatively high and fishing mortality rates being well below the target level of 0.50 (NEFSC 2009).

A stock assessment update was conducted in 2002 by using an age-structured model (i.e., ADAPT-VPA) that was approved by the Stock Assessment Review Committee (SARC) after concerns with previous approaches (Kahn 2002). Previous results showed a severe retrospective bias in estimates of fishing mortality (F) and spawning stock biomass (SSB). The Weakfish Technical Committee (WTC) concluded that the model was underestimating F and overestimating SSB in recent years, and indicating high uncertainties in the parameter estimates (ASMFC 2009). The WTC considered two possible reasons for the weak stock assessment: (i) poor biological sampling of commercial and recreational catch and discard; (ii) impractical assumptions of the age-structured models, for example, catch-at-age matrix is error-free (NEFSC 2009).

In 2003, another assessment of the Weakfish stock was conducted, with the application of biomass dynamic model and age-structured model. However, retrospective bias was still present in both analyses of the Weakfish population, causing concern among stakeholders about the stock assessment method. The WTC also expressed worry about the parameter estimates, since they were not in accordance with observed trends in declining stock structure and catch rates in commercial and recreational fisheries. The Stock Assessment Review Committee (SARC) referred conflicting trends in the fishery data, with discrepancies among fishery-independent surveys, fishery-dependent CPUEs, and catch-at-age data (NEFSC 2009).

The ASMFC passed Amendment 4 to the Weakfish IFMP in 2003 to update management approaches and reflect current conditions of population dynamics. Amendment 4 established a brand new harvest control framework for Weakfish, incorporating multiple biological reference points into a single decision rule for managers (ASMFC 2002). Amendment 4 also mandated the ASMFC with implementing objectives and goals to rebuild the Weakfish stock within six years, if the population is ever found to be overfished (ASMFC 2002).

The stock assessment report began in 2003 and ended in 2006, with several unresolved problems that prevented its confirmation by the ASMFC. However, the Weakfish Management

Board accepted five main points to be used in management that included: (i) the stock is declining, (ii) total mortality is increasing, (iii) little evidence of overfishing, (iv) stock decline is due to something other than exploitation, and (v) management intervention will not reverse the trend in stock abundance (ASMFC 2009).

Since the passing of Amendment 4, four addendums have been approved to improve the management of Weakfish under the ASMFC IFMP. A particularly important one is Addendum II, which was implemented in 2007 as a response to the 2006 stock assessment report (NESFC 2009). According to the 2006 stock assessment, Weakfish abundance had reached its lowest point, with little evidence suggesting increasing fishing mortality or overfishing (ASMFC 2009). Therefore, Addendum II required member states to maintain current fishery regulations, implement a recreational six fish bag limit, and impose a 150 pound commercial bycatch trip limit (ASMFC 2007). They have tried the fishery management in such a way to improve the abundance to reduce natural mortality rates, it is, disappointingly, recognized by the ASMFC that nothing more can be done in the way of regulating the fishery to stop declining trends in the Weakfish stock (ASMFC 2009).

1.6 The stock recruitment of Weakfish

High annual recruitment variation is an important component in fish stock assessment and management. Management strategies should be designed to take the uncertainties of fish populations and their assessments into account. Uncertainties in fishery mainly include estimation uncertainties and future process uncertainties. Estimation uncertainties include all uncertainties about the model structure and the associated parameters. Future uncertainty means how ecological and management processes may change in the future and it has nothing to do with how well we have estimated them in the past. Here, recruitment variation is a form of process uncertainty and a major component of future uncertainty, which can be a significant component of the total uncertainties, particularly when a large proportion of the total population consists of the recruiting year class. Fish populations with different levels of recruitment variability have different risk is of extinction and recovery. One method to evaluate uncertainty from recruitment variation is to assume that future recruitment will occur with a similar distribution and time-series structure to historical recruitment (Maunder and Deriso, 2003). Therefore, it is important to have good estimates of historic recruitment variability when modelling spawning-recruitment relationship.

Due to the complexity of spawning pattern, the recruitment of Weakfish has been found to be affected by many biotic and abiotic factors. Among these environmental factors, the most important are water temperature and flow (Hastie et al., 2003). Changes in temperature potentially affect individual growth, longevity, and reproductive success (Hastie et al., 2003). The increase and decrease of temperature can change the timing of spawning, which might disrupt the timing of fish reproduction cycles.

1.7 Nonstationarity in population processes

The use of stationary model has been common in traditional population dynamics and stock assessment models due to the difficulties in solving nonstationary population dynamics models (Jiao et al., 2010). In recent years, nonstationary processes have been investigated both theoretically and practically in ecological studies (Priestley, 1988; Fu et al., 2001; Turchin, 2003). However, they have seldom been utilized in current fisheries modelling and stock assessments, especially when age-structured models are used (Jiao et al., 2009; 2012). The change in time of effects of some density-independent environmental factors will lead dynamics of a population becomes nonstationary (Royama, 1992). In addition, uncertainties in model selection will be high when a model is directly selected without evaluation against with other possible models, particularly those that include nonstationary processes.

Like other fish species, the value of M of Weakfish was considered as a nonestimable parameter inside of the SCA models, and was assumed to be known (M=0.25) when traditional population assessment models were used (ASMFC, 2006; NDPSWG, 2009; NEFSC, 2009). However, recent work indicates that the M value for Weakfish is not constant, and the ASMFC Weakfish Stock Assessment Subcommittee has been working on how to estimate it (ASMFC, 2006; NEFSC, 2009). The nonstationary process is assigned to the value of natural mortality (M), one of the most uncertain and dominate parameters in fisheries assessment (Vetter, 1988; Clark, 1999). Fortunately, Jiao et al., (2010) have developed a way to estimate M through a nonstationary process, and this approach was also based on Atlantic Weakfish. In this study, I'll explore the "best" operating model on stock-recruitment relationships based on her methods (Jiao et al., 2009; 2012).

1.8 Goals and objectives

The overall goal of my research is to explore spatial differences in CPUE year trend and discern the influence of stock-recruitment model on management strategies evaluation for

Weakfish. More specifically I will do the following: 1) evaluate the performance of spatial, non-spatial, and nonlinear models in analyzing spatial autocorrelation; 2) explore the spatial and temporal abundance variation of Weakfish using standardized catch rate; 3) evaluate the influence of the selection of the stock-recruitment models on MSE.

More specifically, in Chapter 2, I constructed and compared 6 statistical models to NEAMAP survey data to determine which one(s) provide best fitting and predicting. Then I explored the influence of environmental factors in the models. In Chapter 3, I used the best two models selected in the second chapter to compare Weakfish CPUE year trends, in the Chesapeake Bay, inshore area and offshore area and compare the differences between Weakfish relative abundance and environmental factors from all three surveys. In Chapter 4, I conducted a simulation study to explore the "best" operating model on stock-recruitment relationships in MSE process. I also explored the F-based management strategies in managing the Weakfish population based on measurement of risk of overfishing and being overfished.

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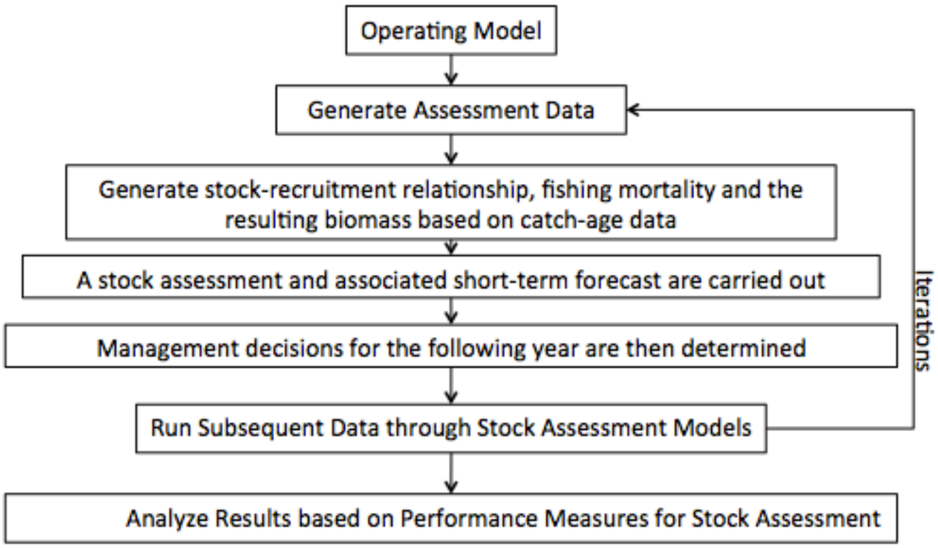

Figure 1.1. A diagram of the proposed simulation study to investigate the influence of model selection in fisheries stock assessment.

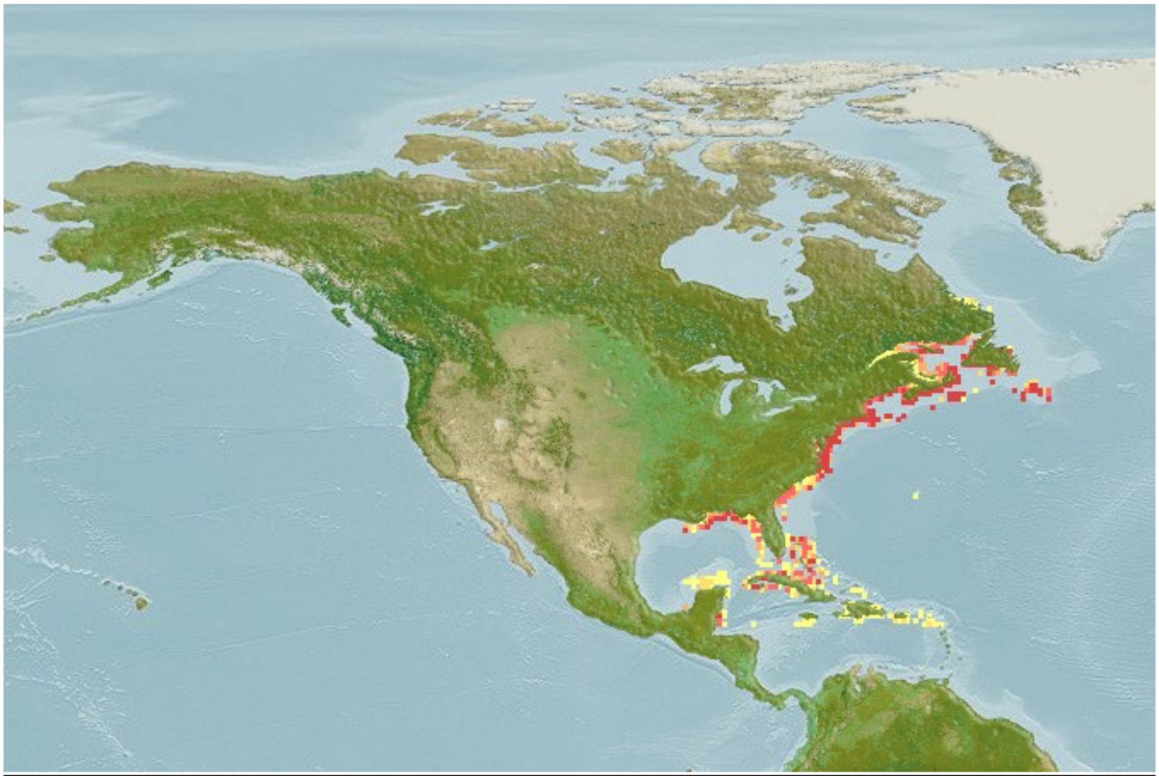

Figure 1.2 Distribution range colors indicate degree of suitability of habitat which can be interpreted as probabilities of occurrence (http://www.fishbase.org/summary/SpeciesSummary.php?ID=406&AT=weakfish).

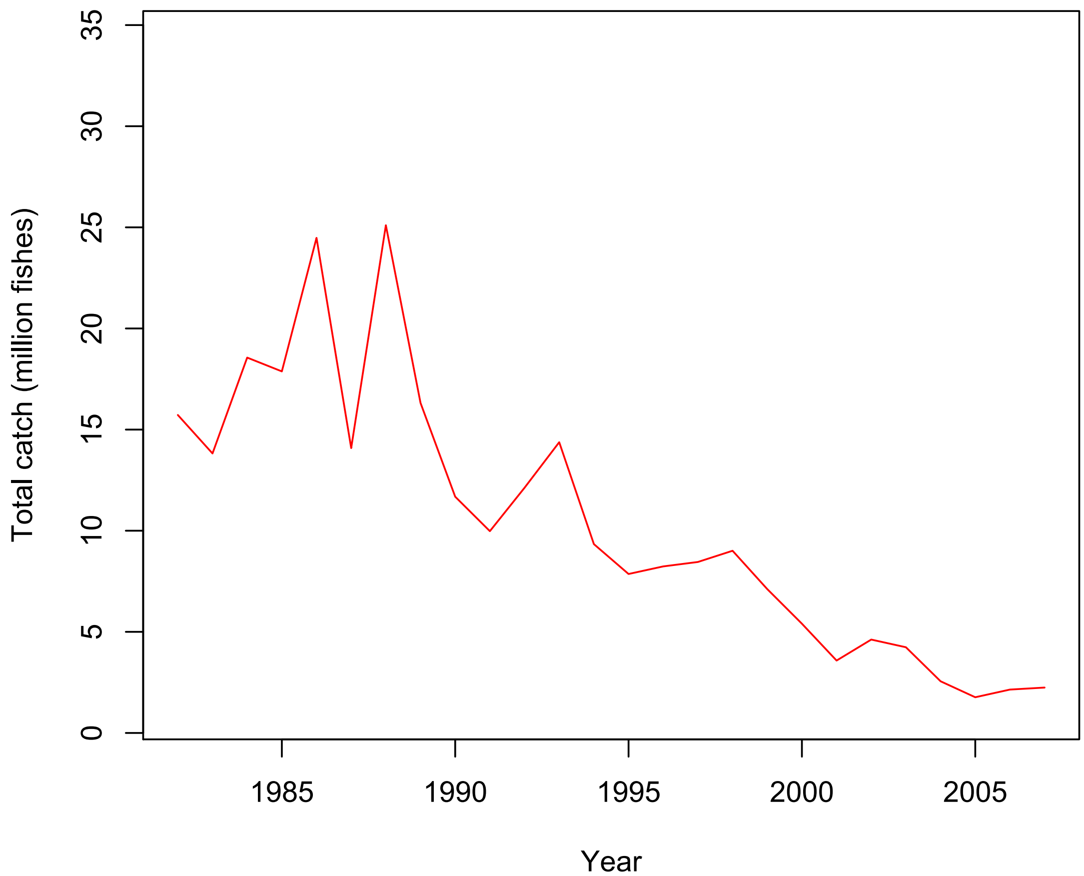

Figure 1.3. Historical catch of Atlantic Weakfish (ASMFC 2009).

Chapter 2

Nonlinearity and spatial autocorrelation in species distribution and modeling: an example based on Atlantic Weakfish (*Cynoscion regalis*)

2.1 Abstract

Spatial autocorrelation (SAC) is frequently observed in fisheries data in which samples collected are not independent from each other at nearby locations. It is a feature of ecological data across a large environmental range. We examined catch rates of Atlantic Weakfish (*Cynoscion regalis*) along the west coast of Atlantic Ocean offshore area, which varies substantially over space and time. Data used in this study were obtained from the Northeast Area Monitoring and Assessment Program (NEAMAP). Because of the high percentage of zero catches in the data, a delta approach was used. Five models were used to test spatial autocorrelation: 1) delta model comprising two generalized linear models (Delta_GLM); 2) delta model comprising two generalized additive models (Delta_GAM); 3) simultaneous autoregressive (SAR) error model combined with auto covariate model; 4) SAR lag model combined with auto covariate model; 5) SAR mixed model combined with auto covariate model. The result from 3-fold cross-validation indicated that the Delta-GAM yielded the smallest training error and testing error followed by the SAR error model combined with auto covariate model. The residual maps also indicate that the Delta-GAM and SAR error model decreased the spatial autocorrelation in the data. We suggest Delta-GAM and SAR error model with auto covariate regression to be alternative to deal with data with nonlinearity and spatial autocorrelation.

2.2 Introduction

Species distributional data, such as biological survey data, are frequently used for analyzing the relationship between species distribution and environmental factors. It can help shape the foundation of species management and conservation procedures by predicting abundance distribution based on future environmental factors and marine-exploration plans. Spatial data analysis was introduced into fisheries during the late 1980s to improve stock assessment for spatially aggregated species (Conan 1985; Gonzalez-Gurriaran et al., 1993). Spatial analysis has been applied for detecting the spatial distribution patterns of fish stocks (Vignaux 1996; Walters et al., 2007).

Spatial autocorrelation (SAC) is a phenomenon in which samples are not independent from each other at nearby locations (Tobler 1970). Multiple factors can cause SAC (Legendre and Fortin 1989; Legendre 1993; Legendre and Legendre 1998), such as biological process (i.e. distance-related dispersal or species interaction), inappropriate nonlinear relationship between environmental factors and species as linear, or failing to incorporate important environmental variables that are spatially distributed (Besag, 1974). The second and the third factors are sometimes considered as spatial dependency, rather than SAC (Legendre et al., 2002).

Generalized linear models (GLMs) and generalized additive models (GAMs) are commonly used in modeling the relationship between catch rates, which is often the number of fishes per tow (or per unit time), and environmental and spatial/temporal factors. The GLMs assume a linear relationship between link function of expected value of response variable and explanatory variables (Maunder and Punt, 2004). In contrast, GAMs are extension of GLMs that use smoothing functions rather than a linear function of explanatory variables, to deal with the nonlinear relationships between a link function of expected value of the response variable and the explanatory variables. A nonlinear relationship is common between catch rates and environmental variables, and this is why GAMs usually perform better than GLMs in exploring the relationship between catch rates and environmental factors.

However, both GLMs and GAMs assume the observed catch rate data are often identically independent in catch rate standardization. This assumption is often violated for migrating fish populations. Because many marine species live and move together: the closer they are, the more similar they are in observation of abundance, which is known as SAC. Thus, SAC is problematic for both species distribution modeling and catch rate standardization when using standard GLM and GAM models. Many other methods have been used to deal with SAC in biological survey data as new trends in modeling species distribution (Zimmerman et al., 2010). One of these is a spatial regressive model, such as simultaneous autoregressive model (SAR), which incorporates spatial weight matrix where the neighborhood of each location and weight of each neighbor is defined into standard linear model. The spatial dependence of a location on neighboring locations is modeled with a variance-covariance matrix (Cressie, 1993; Anselin, 1988; Anselin and Bera, 1988).

In this study, we sought to act in accordance with the Atlantic State Marine Fish Commission (ASMFC) recommendations on Weakfish. The ASMFC advises better identification of environmental influences on Weakfish and to apply catch rate analysis explicitly incorporating environmental variables. Hence, I applied statistical analyses for a dataset from a fishery independent survey in an exploratory way, modeling catch rates of Weakfish as a function of the explanatory variables, in order to identify which of them influence Weakfish catch rate and to quantify their effects. The goals of this study were: 1) to evaluate the performance of spatial, non-spatial, and nonlinear models in analyzing spatial autocorrelation; 2) to explore the influence of environmental factors on west Atlantic Weakfish distribution.

2.3 Material and method

2.3.1 Data

Data used in this study were obtained from a fishery-independent survey, Northeast Area Monitoring and Assessment Program (NEAMAP). The NEAMAP survey database includes 1820 samples from 2007 to 2013. Locations of sample sites ranged from 35.16 to 41.44 ^{0}N and 70.87 to 75.99 ^{0}W. Eighty samples were removed from dataset because of either incorrect records or containing missing values in explanatory variables, reducing the total number of samples to 1740 (Fig 2.1). Nine explanatory variables were available for NEAMAP survey dataset: seven continuous variables: depth, water temperature, percentage of oxygen saturation, salinity, dissolved oxygen, latitude, and longitude; two categorical variables: year and month.

The Spearman correlation among all explanatory variables was examined to detect highly correlated variables. Preliminary stepwise procedure based on Akaike Information Criterion (AIC, Akaike, 1974) was conducted to exclude the one that performed worse in the highly correlated pair. The remaining explanatory variables were further selected through a stepwise selection based on AIC (Akaike, 1974; Burnham and Anderson, 2002). The model with smaller AIC was used in next step. In the situations when ΔAIC is less than 3 comparing to the model with the lowest AIC, a cross validation procedure (see below) was further used to help select variable and compare models. Interactions between environmental factors were not taken into account in the model in order to avoid additional multicollinearity problems and model interpretation difficulties (Maunder and Punt, 2004; Damalas et al., 2007). Variable selection for GLM and GAM was based on the description above. The selected variables were then continuously used in the spatial autoregressive models with further selection.

2.3.2 Generalized linear model (GLM)

A GLM is usually written as:

$$g(E(y)) = \beta_0 + \sum \beta_i x_i \quad (1)$$

where *y* is response variable, β_i is fixed-effect coefficient for variables , x_i is the *i*th environmental variables (Montgomery et al., 2006). The usage of log-transformation of catch rate is common in fisheries and turns out to be appropriate in many circumstances (Quinn and Deriso, 1999). Thus, we used the log-transformed catch rate as the response variable following a normal distribution. Because the NEAMAP dataset included a large number of zero observations (48%), the commonly used normal or lognormal distribution assumption was violated (Ortiz et al., 2000). Thus, Delta-GLM was used here to deal with the problem of high percentage of zero observations in the survey data. A delta model contains two components; one part is to fit the positive observations (Eq 1) and the other to estimate the probability of positive catch (Eq 2). By multiplying these two parts, we abtained the estimation of catch rate from a delta model (Lo et al., 1992; Maunder and Punt, 2004; Murray, 2004; Ortiz et al., 2000; Pennington, 1996; Stefansson, 1996; Ye et al., 2001). In order to estimate the probability of zero observation, values of 0 (no fish capture) and 1 (at least one fish caught) were regarded as Bernoulli variable with a probability q of positive catch. Similarly, q could be estimated by a generalized linear model, which was conducted through a Bernoulli distribution assumption.

$$\Pr(Y = y) = \begin{cases} q & y = 1 \\ 1 - q & otherwi\square e \end{cases} \quad (2)$$

$$ln\left(\frac{q}{1-\hat{q}}\right) = \alpha_0 + \sum \alpha_i x_i \quad (3)$$

where q is the probability of positive observation, α is the regression coefficient vector, x_i is the explanatory variable vector.

2.3.3 Generalized additive model (GAM)

A GAM is a nonparametric generalization of a GLM with additive predictors rather than linear predictors. Generally, GAM is written as:

$$g(E(y)) = \beta_0 + \sum s_i(x_i) \quad (4)$$

where *y* is response variable vector, x_i is explanatory variable vector, s_i is the smoothing function for the explanatory variable *i*. Similarly, we also used the Delta- GAM to deal with the zero observations in the survey dataset.

$$ln\left(\frac{q}{1-\hat{q}}\right) = \alpha_0 + \sum f_i(x_i) \quad (5)$$

where q is the probability of positive observation, f_i is the smoothing function for the explanatory variable x_i.

2.3.4 Autoregressive model

The idea of Delta-GLM was also used here when autocorrelation in the data were considered. For the positive observations, the models with SAC were used. For models to describe catch or not, auto covariate regressions were used (see below).

For normally distributed data in linear models, spatial autocorrelation can be incorporated by autoregressive models such as simultaneous autoregressive model (SAR). SAR models assume that the value of response variable at location p is not only a function of explanatory variable at p, but is also related to a neighboring location q. (Cressie, 1993; Lichstein et al., 2002; Haining, 2003). The neighborhood relationship among each location is expressed in a $n \times n$ binary spatial weight matrix (W), with elements (w_{ij}) being a measurement of connection between p and q. The spatial weight matrix is specified by identifying the neighborhood structure of each cell. Here the neighborhood is identified within the distance of 100 km.

Three different SAR models were compared here based on the occurrence of spatial autocorrelation (Cliff and Ord 1981, Haining 2003). The SAR error model assumes the spatial autocorrelation is found only in the error term. For the SAR error model, generalized linear regression model ($Y = X\beta + \varepsilon$) is amended by a spatial structure term (λW) with the spatial error term (μ):

$$Y = X\beta + \lambda W\mu + \epsilon \qquad (6)$$

where λ is a the spatial autoregression coefficient, W is the spatial weight matrix, β is a vector representing the slopes associated with the predictors in the original predictor matrix X, $\mathcal{E}$ is the identical independent error.

The second model is the SAR lag model, which assumes the autoregression process only occurs in the response variable ("inherent spatial autocorrelation"), and takes a term (ρW) into account for the spatial autocorrelation in response variable.

$$Y = \rho WY + X\beta + \varepsilon \qquad (7)$$

where ρ is the autoregression coefficient, and the remaining terms are as above.

The third model is SAR mixed model, which assumes spatial autocorrelation arises in both response and predictor variables. Under this circumstance, another term ($WX\gamma$) needs to be introduced in the model, which represents the regression coefficients (γ) of spatial lagged explanatory variables (WX).

$$Y = \rho WY + X\beta + WX\gamma + \varepsilon \qquad (8)$$

2.3.5 Auto-covariate regression

Applications of the SAR models in fitting binary data has been found to be limited (Dorman et al., 2007). However, auto-covariate regression is applicable in this situation, which is an extension of generalized linear model by adding a distance-weighted function of neighboring responses. The additional parameter is referred to be auto-covariate, which is applied to capture the spatial autocorrelation. Auto-covariate can be applied to binomial data (Knapp et al., 2003). Here, it is used in the spatial model corresponding to the Eq (3), or Eq(5) in the Delta-GLM and Delta-GAM.

An auto-covariate regression is written as,

$$\log\left(\frac{q}{1-q}\right) = X\beta + \rho A + \varepsilon \tag{9}$$

where q is the probability of a positive observation, β is the fixed-effect coefficient, X is environmental variable, ρ is the covariate of A,

$$A = \frac{\sum_{j\epsilon k} w_{ij} y_j}{\sum_{j\epsilon k} w_{ij}} \text{ (the weighted average)} \tag{10}$$

where, $\boldsymbol{y_j}$ is the response value of y at site *j* among *i's* set of $\boldsymbol{k}$ neighbors; and $\boldsymbol{w_{ij}}$ is the weight given to site *j's* influence over site *i*, and $\boldsymbol{\varepsilon}$ is the error, which is assumed to be identical and independent (Augustin et al., 1996; Gumpertz et al., 1997).

2.3.6 Model evaluation

Three model selection approaches were considered to select the most appropriate model: 1) Akaike's information criterion (AIC); 2) spatial distribution residual map and correlogram plot; 3) cross-validation. AIC deals with model goodness-of-fit and complexity of model; correlogram plot tells the story of Moran's coefficient on distance classes; and cross-validation can assess the performance of model prediction.

2.3.6.1 Akaike's information Criterion (AIC)

Akaike's information criterion (AIC) function is expressed as:

$$AIC = -2\ln(L) + 2p \tag{11}$$

where p is number of parameters in the model, L is the maximized value of the likelihood function for the model. AIC is particularly useful when dealing with the trade-off between model complexity and goodness-of-fit, and the model with minimum AIC value is preferred.

2.3.6.2 Cross-validation

Another procedure to evaluate the performance of each model was k-fold cross-validation (Damalas et al., 2007; Hastie et al., 2001). To conduct k-fold cross-validation, the whole dataset was divided into k sub-datasets with equal size randomly. Each sub-dataset was then used as test dataset to predict, while the remaining k-1 sub-datasets were considered as training data to fit the model. The error from prediction process was called test error, and error from fitting process was called training error.

$$\text{Training (Test) error} = \frac{1}{N}\sum_{l=1}^{N}(y_l - \hat{y}_l)^2 \qquad (12)$$

where N is the number of observations, y_l is the jth observation, and $\hat{y}_l$ is the estimated value. Three-fold cross-validations were performed for the delta model and spatial model. The model producing lower training error and testing error would be preferred (Damalas et al., 2007; Hastie et al., 2001).

2.4 Result

Correlation coefficients among all explanatory variables were calculated and I detected high correlations between longitude and latitude (0.91), dissolved oxygen and percentage of oxygen saturation (0.81), and month and water temperature (0.89) (Fig. 2.2) in the data. Moreover, the preliminary stepwise selection implied that models including latitude yielded smaller AIC value than models including longitude. Models including dissolved oxygen had smaller AIC value than those with percentage of oxygen saturation. Month and water temperature are highly correlated. However the both GLM and GAM with both month and water temperature yielded smallest AIC (Table 2.1). After the cross validation, we found the GLM with month included but not water temperature yielded smaller cross validation error and the GAM with both water temperature and month yielded smaller cross validation error (Table 2.2). Thus, variables longitude, and percentage of oxygen saturation were eliminated before a stepwise selection for all models because of high correlation with latitude and less predictive power. A stepwise procedure was applied to the remaining variables to select variables for the delta models and spatial models. The variables with significant effect (p-value<0.05) and a smaller AIC value were selected into the model (Table 2.3).

From Table 2.4, we can see that among five candidate models, the Delta-GAM model yielded the smallest AIC value when modeling positive values (3885.5), followed by the SAR mixed model (3962.4). Delta- GAM model also yielded the smallest AIC value when estimating the probability of positive catches (1554.1), followed by auto regressive model (1723.4). Delta-GAM model had largest R^2 when modeling positive catch (35.7%) followed by SAR mixed model (31.5%), and estimating probability of non-zero catch (43%) followed by auto regressive model (29.6%).

Residuals of all five candidate models have Moran's I significant (Table 2.4). Spatial correlogram plot (Fig 2.3) showed that spatial autocorrelation exists in the residuals even when spatial models were used. The different models tended to capture spatial autocorrelation of different scales. The SAR mixed model only showed spatial autocorrelation when spatial scale is less than 1.

Residual maps (Fig 2.4) of five candidate models indicate that the residuals from Delta-GAM model and SAR error model were less autocorrelated since there was no large cluster of residuals and quadrate size did not significantly differ from each other. GAM model performed better than SAR error model due to smaller quadrate size. The residual map of SAR mixed model exhibited large clusters of residuals of same sign, suggesting that SAR mixed model did not manage to get rid of all spatial autocorrelation from the observed data. Delta-GLM model, and SAR lag model performed better than SAR mixed model, however, not so well as Delta-GAM and SAR error model.

The model performances of five candidate models were further explored through 3-fold cross-validation (Table 2.5). The Delta-GAM model yielded the smallest training error and testing error on average, followed by SAR error model. This indicated that the Delta- GAM model provided more accurate estimation and prediction than the Delta-GLM model, SAR lag model and SAR mixed model in the example species.

The log-transformed catch rate of Weakfish generally increased from south to north and decreased from west to east (Fig 2.1 and Fig 2.5), while log-transformed catch rate increased from south-to-north approximately from 35^o to 36^o N, and then decreased quickly from south to north from 36^o to 37^o N. The log-transformed catch rate decreased in the deeper water and higher salinity.

2.5 Discussion

Our analyses provide evidence that the Delta-GAM and SAR error model can be applied as alternatives to deal with spatial autocorrelation in the dataset with high percentage of zeroes. Spatial autocorrelation among samples may cause imprecision and inaccuracy in the conventional model analysis, such as generalized linear models. In the spatial models, over-fitting may decrease the prediction ability. Over-fitting usually occurs when a model is excessively complex. The spatial weight matrix created by neighborhood list increases the complexity of in spatial autoregressive models. This spatial weight matrix is able to deal with the spatial autocorrelation very well and increases model fitting, resulting in smaller AIC values than GLM. In this analysis, spatial autoregressive models (SAR error model, SAR lag model, SAR mixed model, and auto covariate regression) yielded smaller AIC values and larger R^2 values than GLMs when both modeling positive catch and probability of non-zero catches. However, from 3-fold cross validation, the training error and testing error from SAR mixed model are much larger than those from Delta-GLM model, indicating over-fitting might be a problem when SAR mixed model was used.

Dealing with zero catches in spatial and non-spatial models is also a well-known problem (Dorman et al., 2007; Li et al., 2011). The zero catch can cause computational difficulties when natural logarithm of catch rate is used in models. Delta models, which have the similar approach of zero-inflated model and hurdle model, are commonly used when large amount of zeroes occur in survey dataset in fisheries. Here Delta-GAM is easy to construct, but for spatial auto regressive models, which can only be fitted when the data is normally distributed, we have to use one model that can both deal with spatial auto correlated error and be fitted by binary data. Here auto covariate regression was used to play the role of sub models with Bernoulli distribution in Delta-GLM and Delta-GAM.

Variable selection is difficult when explanatory variables are collineared. In this study, the SAR models are extended forms of the GLM, thus the variable selection strategies for SAR models are the same as that for GLM. The month and water temperature were highly correlated, and they implied over-fitting in GLM but not in GAM. The reason might be the change of the form of explanatory variables in smooth functions in GAM. The smooth function may turn the variables into parametric or non-parametric forms, resulting in making two linearly dependent variables independent (Wood 2006). In this case, GAM could include one more explanatory variable (water temperature) than GLM.

Every model has its own strengths and weakness, and provides distinctive clarity on the importance of explanatory variables. One of the favorable properties of the Delta-GAM model for the data is that it can yield stable and accurate estimation and prediction without extra effort to deal with the spatial autocorrelation. The advantage of SAR error model is that it managed to deal with the spatial autocorrelation and retain accuracy of estimation and prediction. Though GAM could yield accurate estimation and prediction in this study, it does not mean GAM is better when spatial autocorrelation is incorporated in the data. It is true that GAM model is often preferred in fishery analyses because of its advantages in describing the relationship between fish abundance and environmental factors, which is, however, most likely due to nonlinear relationship in biological context (Damalas et al., 2007). From Figure 2.6, we can see there is a very clear pattern of nonlinear effect from Delta-GAM. Best results should be expected with spatial models, as spatial autocorrelation of Weakfish distribution was anticipated.

In this analysis, the Moran's I values of residuals from the five candidate models were all significant; indicating spatial autocorrelation still existed in the residuals (Fig. 5). The problem might be because of the insufficient explanatory variables, as there were only three environmental explanatory variables considered in the models, and two of them were environmental factors (i.e. salinity and depth). Spatial autocorrelation reveals failure to include important environmental factors in the analysis or inadequate capture of nonlinear effect (Besag et al., 1991; Legendre et al., 2002). Under either circumstance, spatial autocorrelation might make a significant difference for statistical inference (Dormann, 2007; Kelt, 2004). But how to interpret these differences in parameter estimates remains controversial (Dormann, 2007b; Jetz et al., 2005).

In conclusion, Delta-GAM and SAR error models showed good performance for catch rate estimation. Selection of models is determined by the differences of species distribution pattern and available explanatory variables. This may help to understand additional underlying process and factors that affect population dynamics. However, different models are suitable for different situations and objectives. In this study, GAM was preferred in estimating and predicting but may have problems in explaining spatial autocorrelation. The SAR error model explained the spatial autocorrelation better but could not explain the spatial non-linearity very well. Further work may focus on a GAM model with spatial autocorrelation. Further improvement on Weakfish distribution modeling during the survey may be achieved by collecting more environmental variables.

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Table 2.1. Comparison among Weakfish distribution model using three variable selection scenarios. Scenario 1: Null model (only contains intercept); Scenario 2: with month but no water temperature; Scenario 3: with water temperature but no month; Scenario 4: with both water temperature and month.

Scenario	1	2	3	4
GLM	4251.670	3985.481	4002.993	3983.056
GAM	4251.665	3925.756	3886.543	3883.484
SAR err	4236.871	3965.742	3976.557	3961.801
SAR lag	4240.298	3975.591	3989.641	3972.402
SAR mixed	4238.803	3962.369	3977.196	3959.419
GLM prob	2411.800	1741.830	1785.906	1717.443
GAM prob	2411.798	1651.077	1602.359	1554.015
Auto covariate	2177.534	1723.416	1750.618	1723.416

Table 2.2. Training and test errors from four candidate models by 3-fold cross-validation. Delta GLM 1: with month but no water temperature; Delta GLM 2: with both month and water temperature; Delta GAM 1: with water temperature but no month; Delta GAM 2: with both water temperature and month.

Model	Training error				Testing error			
	1	2	3	Average	1	2	3	Average
Delta GLM 1	1.126	1.185	1.172	1.161	1.231	1.144	1.161	1.179
Delta GLM 2	1.159	1.212	1.189	1.186	1.246	1.167	1.202	1.205
Delta GAM 1	1.058	1.103	1.096	1.086	1.149	1.104	1.132	1.128
Delta GAM 2	1.042	1.091	1.086	1.073	1.136	1.096	1.116	1.116

Table 2.3. A stepwise selection based on Akaike Information Criterion (AIC) for five candidate models. Models contained the variables marked with '✓'.

	Delta GLM		Delta GAM		SAR error	SAR lag	SAR mixed	Auto covariate
	Positive	Prob	Positive	Prob				
Latitude	✓	✓	✓	✓	✓	✓	✓	✓
Longitude								
Year	✓	✓	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓	✓	✓
Depth	✓	✓	✓	✓	✓	✓	✓	✓
Water temperature			✓	✓				
Salinity	✓	✓	✓	✓	✓	✓	✓	✓
Dissolved Oxygen								
Percentage of Oxygen Saturation								

Table 2.4. Moran's I value of residuals and statistic tests of five models for NEAMAP survey data (Adjusted R^2 is calculated as $1-\frac{(n-1)SSE}{(n-p)\,SST}$, where n is the number of observations, p is the number of parameters, SSE is sum of squared errors and SST is sum of squared totals).

(a)

Positive	GLM	GAM	SAR error	SAR lag	SAR mixed
AIC	3985.5	3883.5	3965.7	3975.6	3962.4
Adjusted R^2	0.265	0.357	0.292	0.284	0.315

(b)

Probability	GLM	GAM	Auto logistic
AIC	1741.8	1554.1	1723.4
Adjusted R^2	0.287	0.43	0.296

(c)

Model	Delta GLM	Delta GAM	Delta SAR error	Delta SAR lag	Delta SAR mixed
Moran's I	0.026	0.031	0.026	0.029	0.049
p-value of Moran's I	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

Table 2.5. Training and test errors from five candidate models by 3-fold cross-validation.

	Training Error				Testing Error			
Model	1	2	3	Average	1	2	3	Average
Delta-GLM	1.184	1.166	1.132	1.161	1.174	1.163	1.213	1.183
Delta-GAM	1.091	1.037	1.060	1.062	1.165	1.091	1.162	1.139
SAR error	1.192	1.160	1.125	1.159	1.170	1.152	1.203	1.175
SAR lag	1.215	1.173	1.396	1.261	1.175	1.162	1.211	1.183
SAR mixed	1.445	1.269	2.415	1.710	1.244	1.170	1.215	1.210

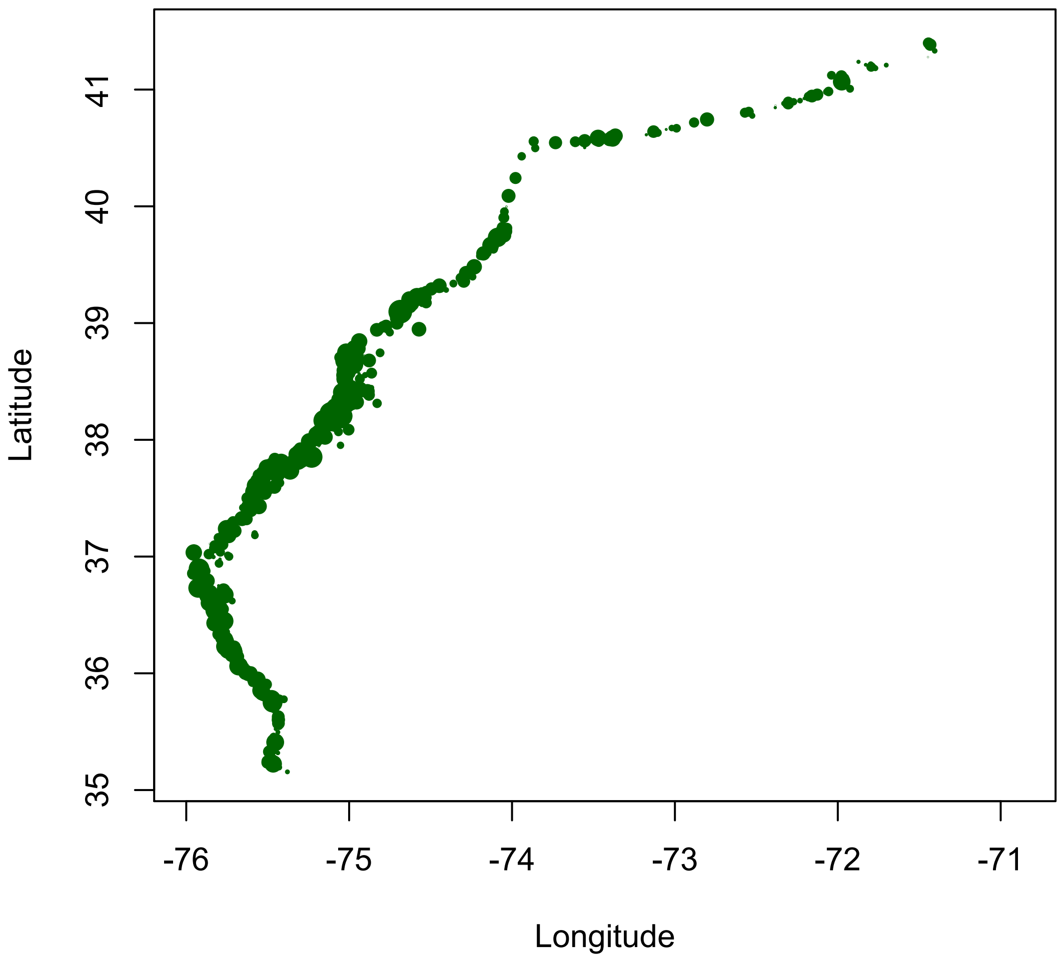

Figure 2.1. Log catch rate distribution map for NEAMAP survey data of Weakfish (2007-2013). Quadrate size is proportional to the value of catch rate.

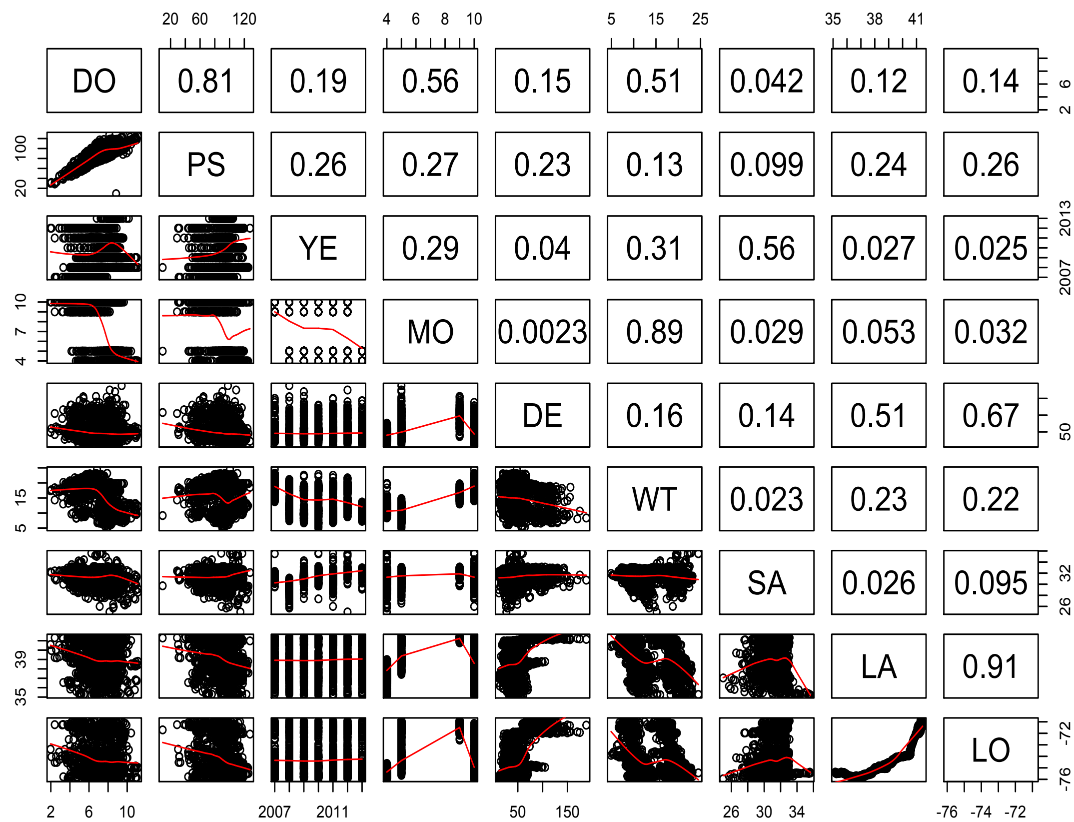

Figure 2.2. Pairwise scatter plots and Pearson correlation coefficients between explanatory variables based on NEAMAP survey data. Abbreviations are as follows: DO=dissolved oxygen, PS=percentage of oxygen saturation, YE=year, MO=month, DE=depth, WT=water temperature, SA=salinity, LA=latitude, LO=longitude.

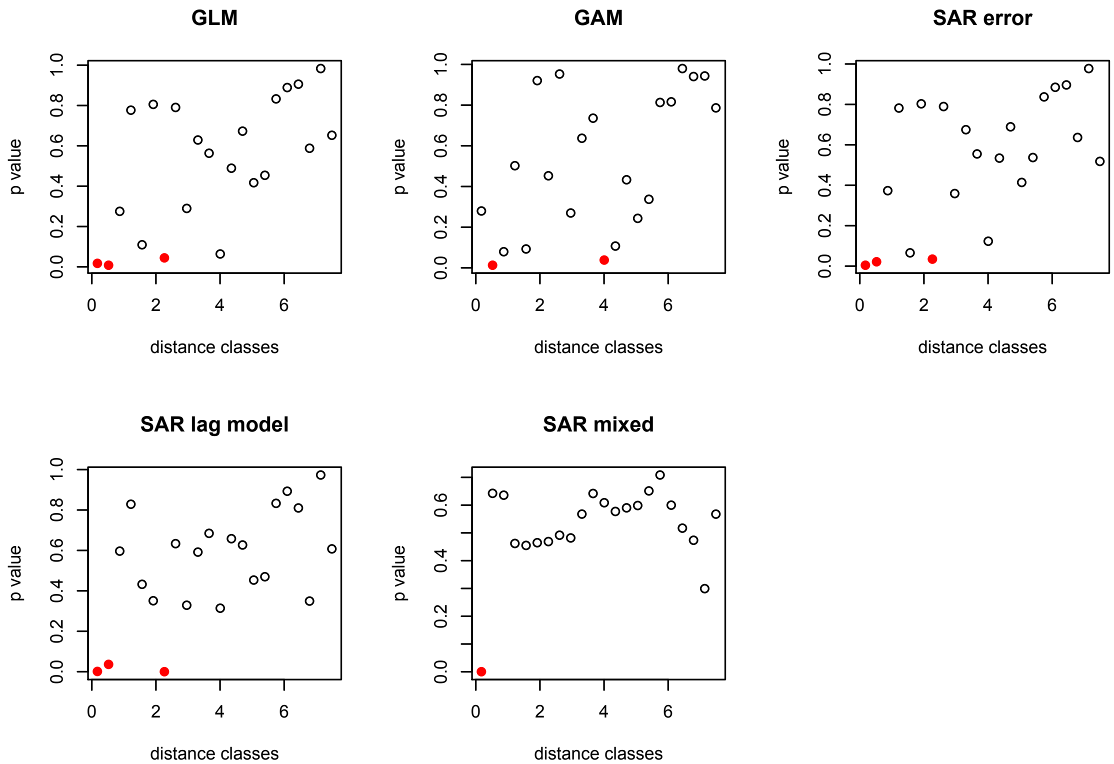

Figure 2.3. P-value of correlation of residuals of five candidate models (i.e. GLM, GAM, SAR error, SAR lag, SAR mixed) for NEAMAP data, highlighted dots represent significant values. 1 distance class refers to 100 km.

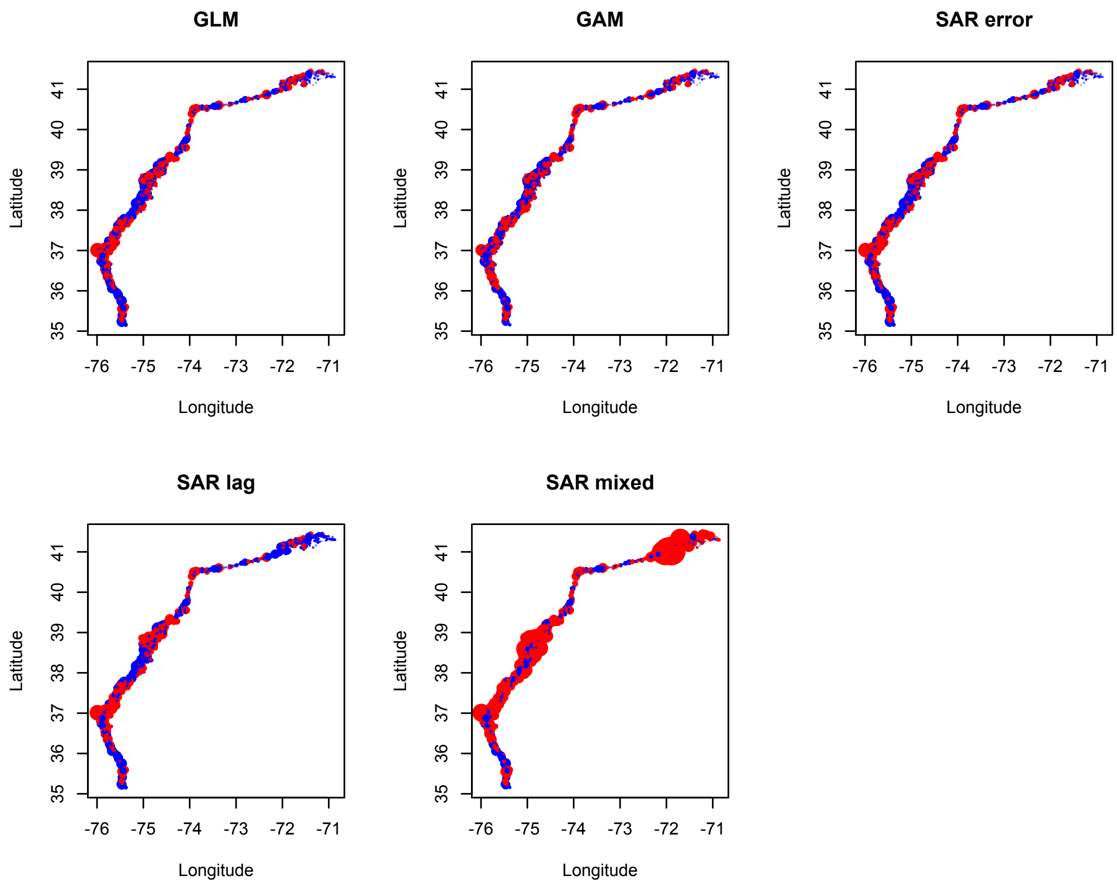

Figure 2.4. Residual maps of five candidate models for NEAMAP survey data. Blue indicates positive, and red indicates negative. Quadrate size is proportional to the value of residuals.

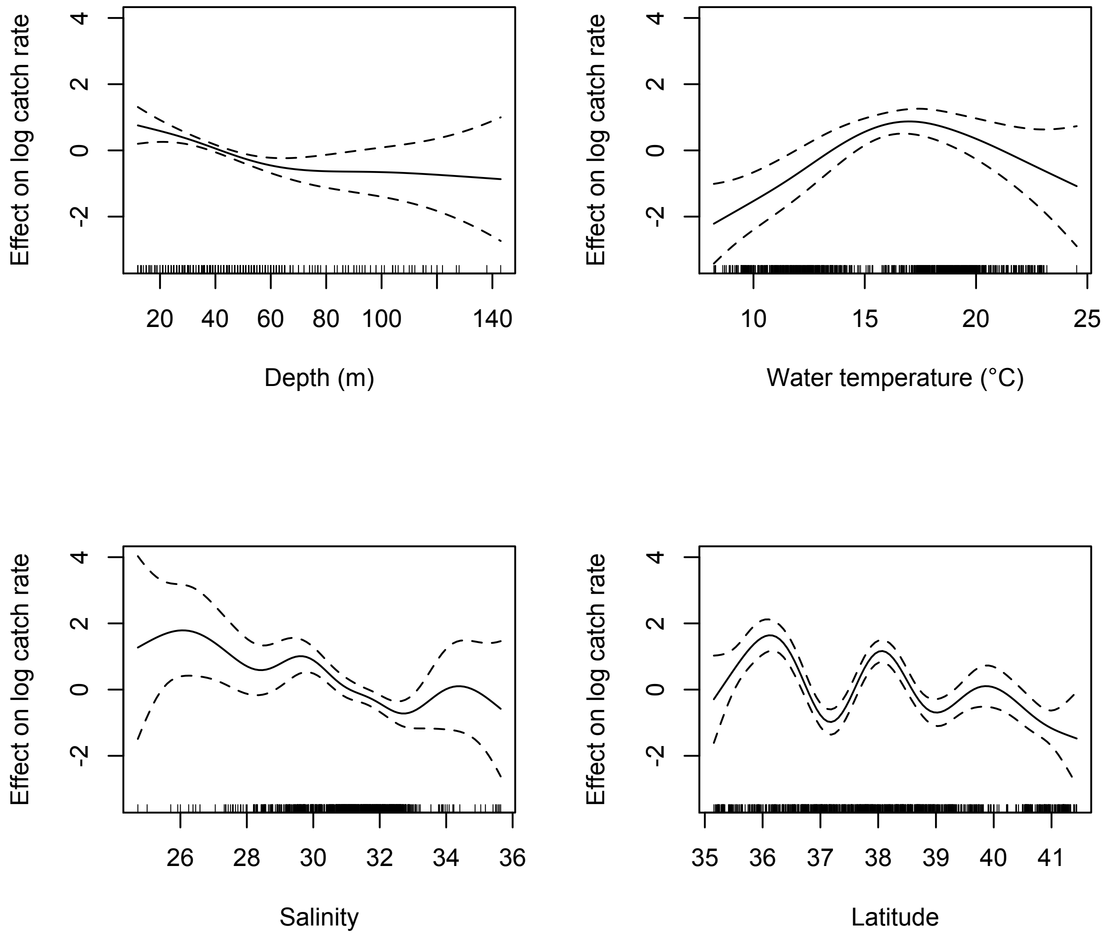

Figure 2.5. Effect of depth, water temperature, salinity, and latitude on log catch rate. Dotted lines around the trend line represent the 95% confidence intervals.

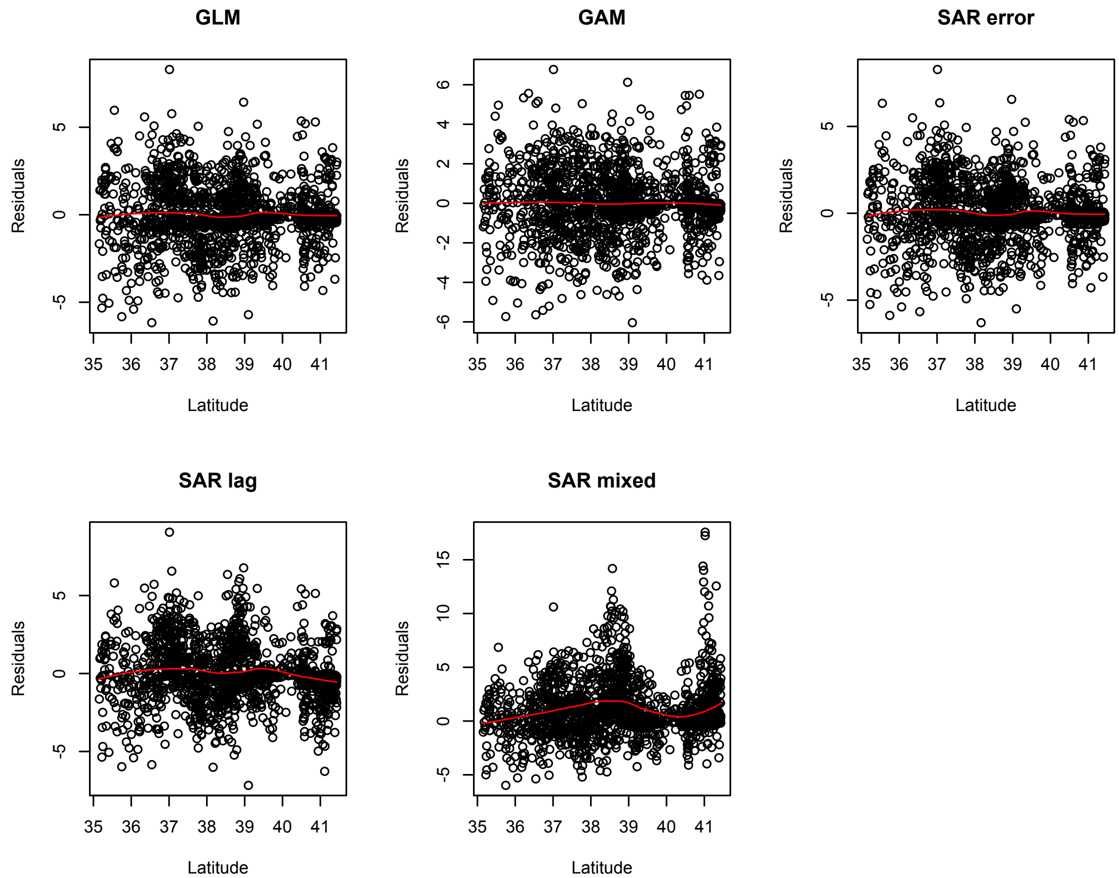

Figure 2.6. Moving average of residuals over latitude for five candidate models.

Chapter 3

Spatial variation of CPUE year trend of Atlantic Weakfish (*Cynoscion regalis*)

3.1 Abstract

Atlantic Weakfish (*Cynoscion regalis*) is an important commercial and recreational species along west Atlantic coast. The trawl net data of Atlantic Weakfish have been collected by several fishery-independent surveys, covering different survey areas and including different environmental variables. However, Weakfish catch rate standardization may face many difficulties, such as high proportion of zero catches, non-linear impacts of environmental factors on fish density, and spatial autocorrelation of fish distribution due to its seasonal migration and wide distribution. In this study, we compared three preliminary selected models: delta-GLM, delta-GAM, and delta-SAR models, on Weakfish catch rate standardization based on three fishery-independent surveys: 1) Northeast Area Monitoring and Assessment Program (NEAMAP); 2) Chesapeake Bay Multispecies monitoring and Assessment Program (CHESMMAP); 3) National Marine Fisheries Service (NMFS) trawl survey for the Atlantic State Marine Fisheries Commission Weakfish Technical Committee (NEFSC, 2009). The AIC values from GAM were smaller than those from the other two models for all three datasets. The AIC values from SAR models were smaller than those from GLM for positive catch, and AIC values from auto logistic models were smaller than from GLM for probability of positive observations for all three datasets. I recommend GAM in modeling year trend of survey CPUE. The standardized catch rates shown as year trend were different when different survey dataset were analyzed. The NMFS trawl, which focuses on deep-water coastal area, showed slightly increasing trend in the mid-2000s. The CHESMMAP, a survey in Chesapeake Bay, year trend showed a decreasing; while NEAMAP, a survey along the coastal area of the western Atlantic, showed a slightly increasing trend by 2013. The differences among the Weakfish relative density to other environmental factors, such as water temperature, salinity and depth, were different in these three surveys also. There are obvious differences in distribution patterns of Weakfish along latitude and longitude from these three surveys. Our study based on the three surveys indicated that there is strong spatial heterogeneity in CPUE year trend even in well-designed surveys. Future stock assessment of Atlantic Weakfish needs to address the spatial variation of CPUE year trend.

3.2 Introduction

Atlantic Weakfish (*Cynoscion regalis*) is a large marine fish that is found along the western coast of the Atlantic Ocean, being the most abundant fish species within the Mid-Atlantic Bight (Shepherd and Grimes 1983). The seasonal migration and wide distribution range are obstacles to abundance estimation and prediction. Catch rate standardization is an important procedure in fish stock assessment because catch rate is an indirect index of the abundance of a species. Variations in the catch rate are inferred to suggest changes to true abundance of the species. An unchangeable catch rate implies sustainable harvesting, while a declining catch rate indicates decreased population or overexploitation. The unstandardized catch rate of Weakfish is not able to reflect its real change of the abundance correctly. Now generalized linear model (GLM) is widely used to standardize the catch rate (Cheng and Gallinat, 2004), but there are many problems in using the GLM, such as ignoring the nonlinear relationship, as well as not taking spatial characteristics into account. Thus, we need a more powerful modeling framework to estimate the abundance indices for Weakfish.

One thing makes the catch rate standardization for Weakfish complicated is its wide distribution as well as complex migration pattern. Weakfish exhibits northerly, inshore migrations during early April, entering estuaries and bays along the eastern U.S. coast to feed and spawn (Lowerre-Barbieri et al., 1995). As water temperatures cool, Weakfish aggregates and moves offshore and to overwintering grounds in southern regions (NEFSC 2009), which occur along the continental shelf from Chesapeake Bay to Cape Lookout, North Carolina (ASMFC 2004). Multiple surveys covering different areas have been conducted to measure the environmental factors and catch rate. The Weakfish living in offshore area may have different habitat preferences than those that live inshore and bay area. In this case, it may be most appropriate to use different models to standardize the catch rate of Weakfish.

GLM is frequently used in exploring the relationship between catch rate and environmental factors. However there are many problems in using the GLM only. One unavoidable problem in fishery-independent surveys for Weakfish is zero observations, which may create problems for estimating catch rate or variable selection when doing log-transformation. Delta models are based on delta-distribution and are often used to deal with zero-catches in fish catch rate standardization (Lo 1992; Punt et al., 2000; Maunder and Punt 2004). The basic idea of delta models is to divide the dataset into two components, one is zero observations and the other is on non-zero (positive) observations. Then the non-zero observations can be modeled based on appropriate assumptions and logistic models will be used to model the presence and absence data. Finally, the prediction of catch rate can be obtained by combining these two models (Lo, 1992).

Another complicating factor is the spatial autocorrelation in the observations, measuring that the observations spatially close to each other are more similar than those that are further apart (Tobler 1970). One major problem of spatial autocorrelation is it violates the basic assumption of independence among observations, which may make the result misleading. Simultaneous autoregressive models (SARs) are commonly used to solve this problem (Dormann et al., 2007). SARs, which incorporate spatial weight matrix where the neighborhood of each location and weight of each neighbor is defined into standard linear model, assume that the observation is not only the function of explanatory variables but also the function of the neighboring observations in space (Cressie 1993). In general, there are three types of SARs: lagged-response model, lagged-mixed model, and spatial error model (Haining 2003; Dormann et al., 2007). Among them, spatial error model has proved better than the other two types of SARs for dealing with spatially autocorrelated species distribution data (Kissling and Carl 2007). In this study we only considered SAR spatial error model after preliminary studies on the three survey datasets (Chapter 2).

In addition, the relationship between response and explanatory variables is usually not linear (Maunder and Punt 2004). If the relationship between abundance indices and environment factors were nonlinear, everything would be different. Linear models can no longer be used here, but generalized additive model (GAM) is able to deal with the nonlinear relationships by introducing smoothing functions of predictor variables rather than linear predictor (Hastie et al., 2001, Wood 2006). The predictor variables can be modeled as parametric, or non-parametric, or semi-parametric form, so that the nonlinearity can be analyzed (Wood 2006).

In this study, I fitted the models, i.e. delta-GLM, delta-GAM and delta-SAR models developed in previous studies, with three different fishery-independent datasets, which were collected in different areas. The goals of this study include the following, (1) explore the spatial and temporal abundance variation of Weakfish using standardized catch rate; (2) compare the performance of delta-GAM and delta-SAR on catch rate standardization; 3) compare Weakfish abundance indices, the CPUE year trends, in the Chesapeake Bay, inshore area and offshore area; 4) compare the differences between Weakfish relative abundance and environmental factors.

3.3 Materials and Method

3.3.1 Data

Data used in this study were obtained from the fishery-independent surveys: 1) Northeast Area Monitoring and Assessment Program (NEAMAP); 2) Chesapeake Bay Multispecies monitoring and Assessment Program (CHESMMAP); 3) National Marine Fisheries Service (NMFS) trawl survey Atlantic State Marine Fisheries Commission Weakfish Technical Committee (NEFSC, 2009). The CHESMMAP survey database includes 4220 samples from 2002 to 2013. Samples ranged from 36.93 to 39.30^{o} N and 75.93 to 76.52^{o} W (Figure 3.1). The environmental variable also only includes depth. There are ten missing values in longitude, latitude and depth, reducing the total number of data entries analyzed to 4210. The NEAMAP survey database includes 1820 samples from 2007 to 2013. Samples ranged from 35.16 to 41.44^{o} N and 70.87 to 75.99^{o} W (Figure 3.2). The environmental variable only includes depth. Two samples were removed from analyses due to missing data entries. The NMFS trawl survey includes 1894 samples from 1972 to 2006. Samples ranged from 34.90 to 41.60^{o} N and 69.52 to 76.07^{o} W (Figure 3.3). The environmental variable includes depth and bottom temperature. But bottom temperature has 328 missing values, and another 49 samples were also excluded due to far distance away from the main area, reducing the total number to 1517.

These three datasets included a large number of zero observations (49% for NEAMAP, 70% for CHESMMAP, 37% for NMFS), and as a result the commonly used normal or lognormal distribution assumptions were violated (Ortiz et al., 2000). Five explanatory variables were available for NEAMAP survey dataset: three continuous variables: depth, latitude, and longitude; two categorical variables: year, and month. Eight explanatory variables were available for CHESMMAP survey dataset: three continuous variables: depth, latitude, and longitude; five categorical variables: year, month, tide, current direction, and current speed. Six explanatory variables were available for NMFS survey dataset: four continuous variables: depth, bottom temperature, latitude, and longitude; two categorical variables: year, and month.

The Pearson correlation analysis among all explanatory variables was examined to detect highly correlated variables. A preliminary stepwise procedure based on Akaike Information Criterion (AIC, Akaike, 1974) was conducted to exclude one of the highly correlated variables.

The remaining explanatory variables were further selected through a stepwise selection based on AIC (Akaike, 1974; Burnham and Anderson, 2002). The model with smaller AIC was used in the next step. Interaction factors were not taken into account in the model in order to avoid additional multicollinearity problems and model interpretation difficulties (Damalas et al., 2007; Maunder and Punt, 2004).

3.3.2 Generalized linear model (GLM)

A GLM is usually written as:

$$y = \beta_0 + \sum \beta_i x_i \tag{1}$$

where y is response variable, β_i is fixed-effect coefficient for variables , x_i is the ith environmental variables (Montgomery et al., 2006). The usage of log-transformation of catch rate is common in fisheries and turns out to be appropriate in many circumstances (Quinn and Deriso, 1999). Thus, we used the log-transformed catch rate as response following a normal distribution. Because the NEAMAP dataset included a large number of zero observations (48%), the commonly used normal or lognormal distribution assumption was violated (Ortiz et al., 2000). Thus, Delta-GLM was used here to deal with the problem of high percentage of zero observations in the survey data (838 out of 1740 zero observations). A delta model usually contains two components; one part is to fit the positive observations (eq 1) and the other to estimate the probability of positive catch (eq 2). By multiplying these two parts, we obtain the estimation of catch rate from a delta model (Lo et al., 1992; Maunder and Punt, 2004; Murray, 2004; Ortiz et al., 2000; Pennington, 1996; Stefansson, 1996; Ye et al., 2001). In order to estimate the probability of positive observation, values of 0 (no fish capture) and 1 (at least one fish caught) were regarded as Bernoulli variable with a probability q of positive catch. Similarly, q could be estimated by a generalized linear model, which was conducted through a Bernoulli distribution assumption.

$$\Pr(Y = y) = \begin{cases} q & y = 1 \\ 1 - q & y = 0 \end{cases} \tag{2}$$

where q is the probability that an observation comes from the binary component.

$$ln\left(\frac{\hat{q}}{1-\hat{q}}\right) = \alpha_0 + \sum \alpha_i x_i \tag{3}$$

where $\hat{q}$ is the probability of positive observations, α is the regression coefficient vector, x_i is the explanatory variable vector.

3.3.3 General additive model (GAM)

A GAM is a nonparametric generalization of a GLM with additive predictors rather than linear predictors. Generally, GAM is written as:

$$y = \beta_0 + \sum s_i(x_i) \tag{4}$$

where y is response variable vector, x_i is explanatory variable vector, s_i is the smoothing function for the explanatory variable i. Similar with the GLM, GAM was also transformed into a Delta- GAM to deal with the zero observations in the survey dataset.

$$ln\left(\frac{\hat{q}}{1-\hat{q}}\right) = \alpha_0 + \sum f_i(x_i) \tag{5}$$

where $\hat{q}$ is the probability of positive observations, f_i is the smoothing function for the explanatory variable x_i.

3.3.4 Autoregressive model

The idea of Delta-GAM was continuously used here when autocorrelation in the data were considered. For the positive observations, the models with SAC were used. For models to describe catch or not, auto covariate regressions were used (see below).

For normally distributed data in linear models, spatial autocorrelation can be incorporated by autoregressive models such as simultaneous autoregressive model (SAR). SAR models assume that the value of response variable at location *i* is not only a function of explanatory variable at *i*, but is also related to a neighboring locations *j* (Cressie, 1993; Lichstein et al., 2002; Haining, 2003). The neighborhood relationship among each location is expressed in a $n \times n$ spatial weight matrix (W), with elements (w_{ij}) being a measurement of connection between i and j. The spatial weight matrix is specified by identifying the neighborhood structure of each cell. Here the neighborhood is identified within the distance of 100 km.

Three different SAR models were compared here based on the occurrence of spatial autocorrelation (Cliff and Ord 1981, Haining 2003). The SAR error model assumes the spatial autocorrelation is found only in error term. For the SAR error model, general linear regression model ($Y = X\beta + \varepsilon$) is amended by a spatial structure term (λW) with the spatial error term (μ):

$$Y = X\beta + \lambda W\mu + \varepsilon \tag{6}$$

where λ is a the spatial autoregression coefficient, W is the spatial weight matrix, β is a vector representing the slopes associated with the predictors in the original predictor matrix X, ε is the identical independent error.

3.3.5 Auto-covariate regression

Applied approach (SAR models) in fitting binary data has been found to be limited (Dorman et al., 2007). However, auto-covariate regression is applicable in this situation, which is an extension of generalized linear model by adding a distance-weighted function of neighboring responses. The additional parameter is referred to be auto-covariate, which is applied to capture the spatial autocorrelation. Auto-covariate can be applied to binomial data (Knapp et al., 2003). Here, it is used in the spatial model corresponding to the eq (3), or eq(5) in the Delta-GLM and Delta-GAM.

An auto-covariate regression is written as,

$$y = X\beta + \rho A + \varepsilon \qquad (7)$$

where y is the response, β is fixed-effect coefficient, X is environmental variables, ρ is the covariate of A,

$$A = \frac{\sum_{j\epsilon k} w_{ij} y_j}{\sum_{j\epsilon k} w_{ij}} \text{ (the weighted average)} \qquad (8)$$

where, y_j is the response value of y at site j among i's set of k_i neighbors; and w_{ij} is the weight given to site j's influence over site i, and ε is the error, which is assumed to be identical and independent (Augustin et al., 1996; Gumpertz et al., 1997).

3.3.6 Akaike's information Criterion (AIC)

Model evaluation helps us to recognize a best model, but only a few model selection approaches have been applied for spatial autocorrelation data. Here, AIC (Akaike's information criterion) was used to compare models. AIC function is expressed as:

$$AIC = -2\ln(L) + 2p) \qquad (9)$$

where p is number of parameters in the model, L is the maximized value of the likelihood function for the model. AIC is particularly useful when dealing with the trade-off between model complexity and goodness-of-fit, and the model with minimum AIC value is preferred.

3.4 Result

Among the three delta models, models to estimate the catch rates when only positive values were analyzed explained 3.4-6.1% for CHESMMAP, 22.7-28.9% of the deviance for NEAMAP, and 21.6-30.6% for NMFS, and the model to estimate the probability of non-zero captures explained 26.8-38.8% for CHESMMAP, 27.8-36.5% of the deviance for NEAMAP, and 23.5-39.9% for NMFS (Table 3.1). Among the six candidate models, the GAM yielded smallest AIC value when modeling positive values for CHESMMAP, NEAMAP, and NMFS, and estimating probability of non-zero catch for CHESMMAP, NEAMAP, and NMFS. GAM model had largest R^2 when modeling positive catch for CHESMMAP, NEAMAP, and NMFS, and estimating probability of non-zero catch for CHESMMAP and NMFS, while auto logistic model had largest R^2 in estimating probability of non-zero catch for NEAMAP.

In CHESSMAP correlation coefficients among all explanatory variables were calculated and I detected high correlations among longitude, latitude, and salinity in the data (Fig 3.4). Moreover, the preliminary stepwise selection implied that models including latitude yielded smaller AIC value than models including longitude in GLM, and salinity is no longer highly correlated with latitude when longitude is not included in the model. However, GAM that included latitude, longitude, and salinity yielded smallest AIC. Thus, the longitude variable was eliminated before a stepwise selection for GLM due to high correlation with latitude and less predictive power. A stepwise procedure was applied to the remaining variables to select variables for the delta models. The variables with significant effect (p-value<0.05) and a smaller AIC value were selected into the model. Similarly, the predictor variables were selected in NEAMAP and NMFS dataset by the same steps.

After variable selection, the final positive catch models and logistic models used different explanatory variables for these three datasets (Table 3.2). The variable year was a categorical variable, and it had to be retained in the model to predict the year trend. The variable month was not in all positive catch models but was kept in all three logistic models in CHESMMAP; it was significant in all the models in NEAMAP but in none of the models in NMFS. Variable depth was significant in every model in the three datasets. Water temperature was significant in every model in CHESMMAP and NMFS, but not significant in GLM in NEAMAP. Dissolved Oxygen was important in CHESMMAP while not important in NEAMAP.

The standardized catch rates from delta-GLM, delta-GAM and delta-SAR, nominal mean, and geometric mean showed similar patterns based on the CHESMAP data from 2002 to 2013 (Fig 3.7). The highest values were all observed in 2004 and the lowest values happened in 2013. From 2004 to 2008, the estimates decreased and varied slightly from 2008 to 2013. The standardized catch rates from delta-GLM, delta-GAM and delta-SAR, nominal mean, and geometric mean showed different patterns based on the NEAMAP data from 2007 to 2013 (Fig 3.8). The catch rates were high in early stage and achieved the maximum at 2011, but then decreased very quickly. All the three models were in the same trend with the nominal mean before 2011; after 2011 the predicted value increased rather than decrease. The standardized catch rates from delta-GLM, delta-GAM and delta-SAR, nominal mean, and geometric mean were similar in year trend based on the NMFS data from 1972 to 2006 (Fig 3.9). In 1995, these four estimated catch rates were all high. In 1994 and 2003, delta SAR gave the highest value than the other two models while GAM was the lowest. In 1978 and 1981, the nominal mean was much higher than the other three estimates. The trends of standardized positive catch for three datasets were very similar with the trends in standardized catch rate (Fig 3.10 - Fig 3.12).

The probability of positive observations of these three surveys varied over time and space. In general, the probabilities estimated from GAMs were larger than those from SARs and GLMs. Based on the CHESMMAP dataset, the probability estimated from GLM was closest to the nominal means compared with other two models, which were larger than that from SARs and smaller than that from GAM (Fig 3.13). Based on the NEAMAP dataset, the largest difference of probability estimated from models and nominal mean was in 2013. The estimated values were approximately around 90%, while the nominal mean was only about 60%. And that was due to the dramatic increase after 2011 (Fig 3.14). Based on NMFS survey, from 1976 to 1986, the probabilities were at relative high levels (> 50%); from 1987 to 1994, the probability were at a relatively low level (<50%); in 1995, the probability reached a high level of about 0.9 and then dropped to about 0.4 in 1996; from 1997 to 2006, the probabilities were between 60%~ 90% (Fig 3.15).

From Fig 3.16 to Fig 3.18, we can see that the log transformed catch rate generally increased from south to north and decreased from west to east for NEAMAP and NMFS, while log catch rate increased from south-to-north approximately from 37^{o} to 37.5^{o} N, and then decreased quickly from south to north, and varied intermittently with longitude over the range of survey for CHESMMAP. The log catch rate decreased in the deeper water for NEAMAP and NMFS survey, and generally increased in the deeper water for CHESMMAP.

3.4 Discussion

In this study, the Weakfish data were collected by three different surveys. The environmental factors that might have significant effect on distribution and abundance were different due to various survey areas. For example, the variable month was never a significant variable in NMFS, but played important roles in some models in the other two datasets. This might be because the data of NMFS were collected only in the fall (September, October and November). Thus, the month effect may not be very significant. Also, variable dissolved oxygen (DO) was included in all the models in CHESMMAP, but in none of models in NEAMAP. This implies that DO may only be a limiting factor in Chesapeake Bay for Weakfish distribution.

The significant factors that were in the same dataset still varied from model to model as a result of different variable selection mechanisms. In this study, since the SAR model and auto logistic model were developed over the GLMs by adding a spatial neighborhood structure, they followed the same variable selection strategy with the two GLMs. In CHESMMAP survey data, latitude, longitude and salinity were detected to be multicolinear. In GLM for positive catch, we dropped longitude and salinity; in logistic regression, we dropped longitude and latitude by stepwise selection. But two GAMs were able to include all the three variables. The reason might be the change of the form of explanatory variables in smooth functions in GAM. The smooth function may turn the variables into parametric or non-parametric forms, resulting in making these three linearly dependent variables independent (Wood 2006). In this case, GAM could include more explanatory variable than GLM. Similar situation also happened in the other two datasets.

The catch rate standardization is critical for Weakfish stock assessment and management because it provides indirect information about the year trend of the population. However, this work is facing challenges since there are several state or federal agencies collecting the fishery-independent survey data every year. Some of them use different gear type (i.e., trawl net or gillnet) and mesh size, record different environmental factors, as well as sample in different seasons (i.e., spring or fall)(WTG 2009). In this study, CHESMMAP, NEAMAP and NMFS were collected by three different agencies. The environmental variables in CHESMMAP and NEAMAP are similar, but are quite different from those collected by NMFS. CHESMMAP focused on the area of Chesapeake Bay, NEAMAP collected data on offshore area of West Atlantic, while NMFS sampled observations at coastal area. In addition, the starting times are also very different: CHESMMAP started from 2002, NEAMAP started from 2007, while NMFS started from 1972. This would make the results of year trend less comparable.

So far the delta-GLM and delta-GAM were commonly compared for Weakfish catch rate standardization, and it turned out that the delta-GAM performed better than the delta-GLM (WTG 2009). Although some other models have been introduced for catch rate standardization such as Tweedie GAM, AdaBoost, etc. They have not been tested based on Weakfish survey data. In this study, both delta-GLM and delta-GAM are not always better than delta-SAR based on AIC and catch rates. Delta-SAR even sometimes shows some superiority over delta-GLM. This might be owing to the wide temporal and spatial range and different spatial structure over time. Thus, future work can be continue trying different models on catch rate standardization, such as Tweedie GAM, AdaBoost based on different ranges, but the "best" model may not be the same one for all surveys.

The methods to deal with a large proportion of zeroes should be paid more attention. Several methods have been developed to handle the zero-observation problem in fisheries (Mark and Maunder 2004). Traditionally, when the proportion of zeroes is small, the original values are often added by a constant before they are log-transformed; when the proportion of zeros is high, two-step models are usually applied, such as delta-model, zero-inflated models and hurdle models (Mark and Maunder 2004). However due to the complexity of two-step models, the estimates of logistic models are not always consistent with different assumptions. In the present study, the probability of non-zero catches in each year from GAMs is mostly larger than that from SARs. There are some distribution assumptions, such as Tweedie distribution, that are reported to be able to handle zero-inflation problem (Soho 2008b). Some one-step models can also be used to deal with zero-inflation, such as quasi-Poisson regression (Ver Hoef and Frost 2003). Again none of them can be suitable for all kinds of fishery data. Currently a framework is suggested to be developed for selecting models dealing with high percent zeros, nonlinearity and spatial characteristics.

In the present study, we compared the performance of delta-GLM, delta-GAMs and delta-SAR on Weakfish catch rate standardization based on three fishery-independent surveys. None of them is completely superior to the other according to multiple criteria. In general, delta-GAMs performed better which implied that nonlinearity is important in understanding Weakfish distribution and year trend analysis. My study also found that the nonlinearity between Weakfish relative density and environmental factors are not the same among different surveys or different distribution areas. There are obvious differences in distribution pattern of Weakfish along latitude and longitude from these three surveys also. My study based on the three surveys indicated that there are strong spatial heterogeneity in CPUE year trend even in well-designed surveys. Future stock assessment of Atlantic Weakfish needs to address the spatial variation of CPUE year trend.

3.6 Acknowledgement

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Table 3.1. AIC values and R^2 of three delta models (i.e., delta-GLM, delta-GAM, delta-SAR) for three datasets.

	Delta GLM		Delta GAM		SAR	Auto
	Positive	Prob	Positive	Prob	error	logistic
CHESMMAP						
AIC	4237.75	3363.61	4179.42	2698.32	4227.64	2974.85
R^2	0.034	0.268	0.061	0.388	0.046	0.308
NEAMAP						
AIC	3985.48	1741.83	3925.75	1651.07	3965.74	1723.41
R^2	0.227	0.278	0.289	0.365	0.262	0.384
NMFS						
AIC	4083.48	1629.86	3787.48	1411.70	3887.57	1524.27
R^2	0.216	0.235	0.306	0.399	0.275	0.346

Table 3.2. A stepwise selection based on Akaike Information Criterion (AIC) for three delta models. Models contained the variables marked with '✓'.

	Delta GLM		Delta GAM		SAR	Auto
	Positive	Prob	Positive	Prob	error	logistic
CHESMMAP						
Latitude	✓		✓	✓	✓	
Longitude			✓	✓		
Year	✓	✓	✓	✓	✓	✓
Month		✓		✓		✓
Depth	✓	✓	✓	✓	✓	✓
Water temperature	✓	✓	✓	✓	✓	✓
Salinity		✓	✓	✓		✓
Dissolved Oxygen	✓	✓	✓	✓	✓	✓
NEAMAP						
Latitude	✓	✓	✓	✓	✓	✓
Longitude						
Year	✓	✓	✓	✓	✓	✓
Month	✓	✓	✓	✓	✓	✓
Depth	✓	✓	✓	✓	✓	✓
Water temperature			✓	✓		
Salinity	✓	✓	✓	✓	✓	✓
Dissolved Oxygen						
Percentage of Oxygen Saturation						
NMFS						
Latitude	✓		✓	✓	✓	
Longitude		✓	✓	✓		✓
Year	✓	✓	✓	✓	✓	✓
Month						
Depth	✓	✓	✓	✓	✓	✓
Bottom temperature	✓	✓	✓	✓	✓	✓

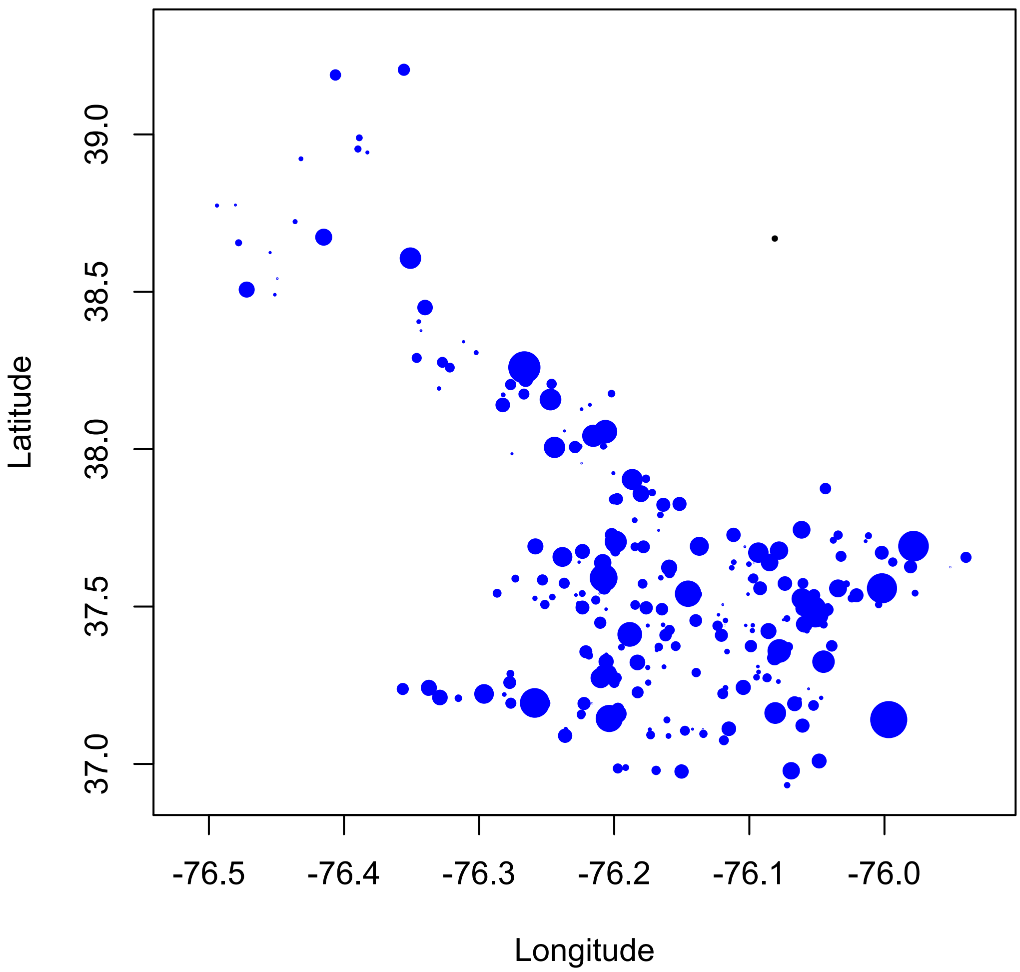

Figure 3.1. Raw catch rate distribution map for CHESMMAP survey data. Quadrate size is proportional to the value of the mean catch rate.

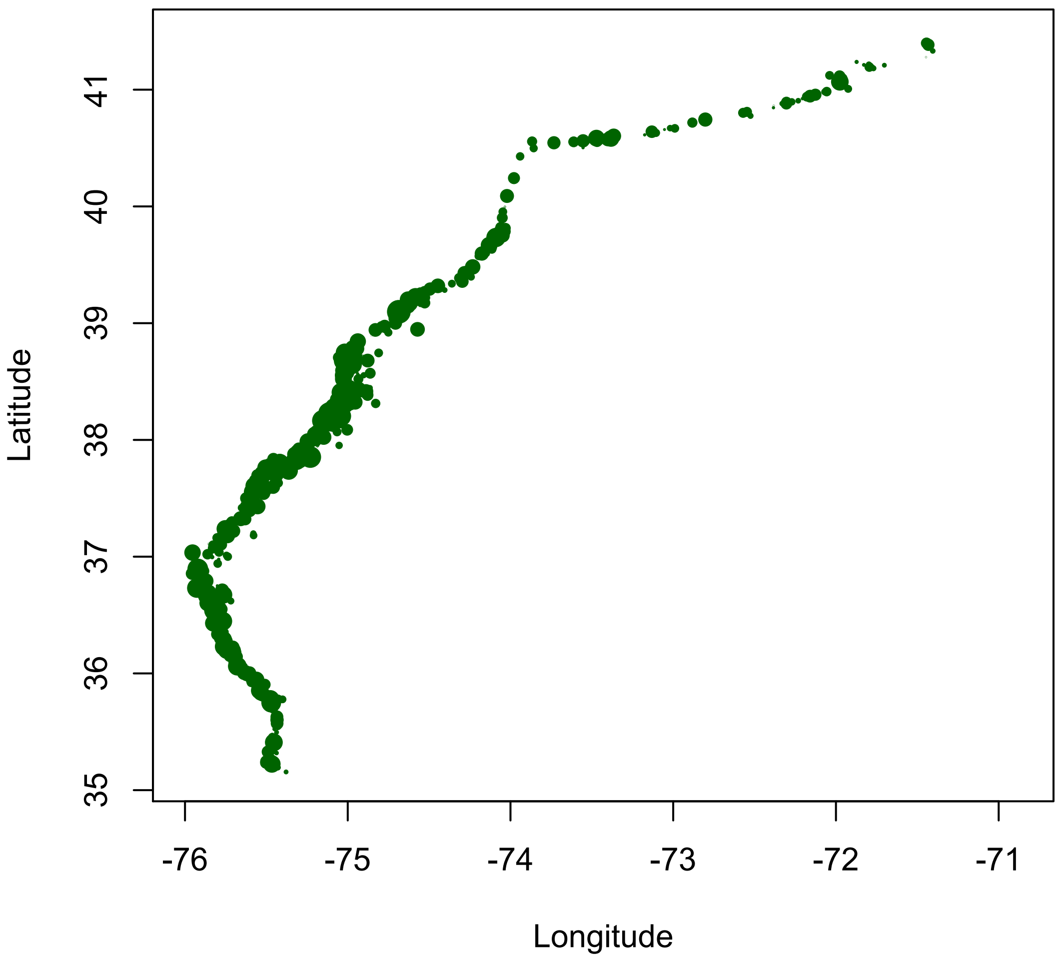

Figure 3.2. Raw catch rate distribution map for NEAMAP survey data. Quadrate size is proportional to the value of the mean catch rate.

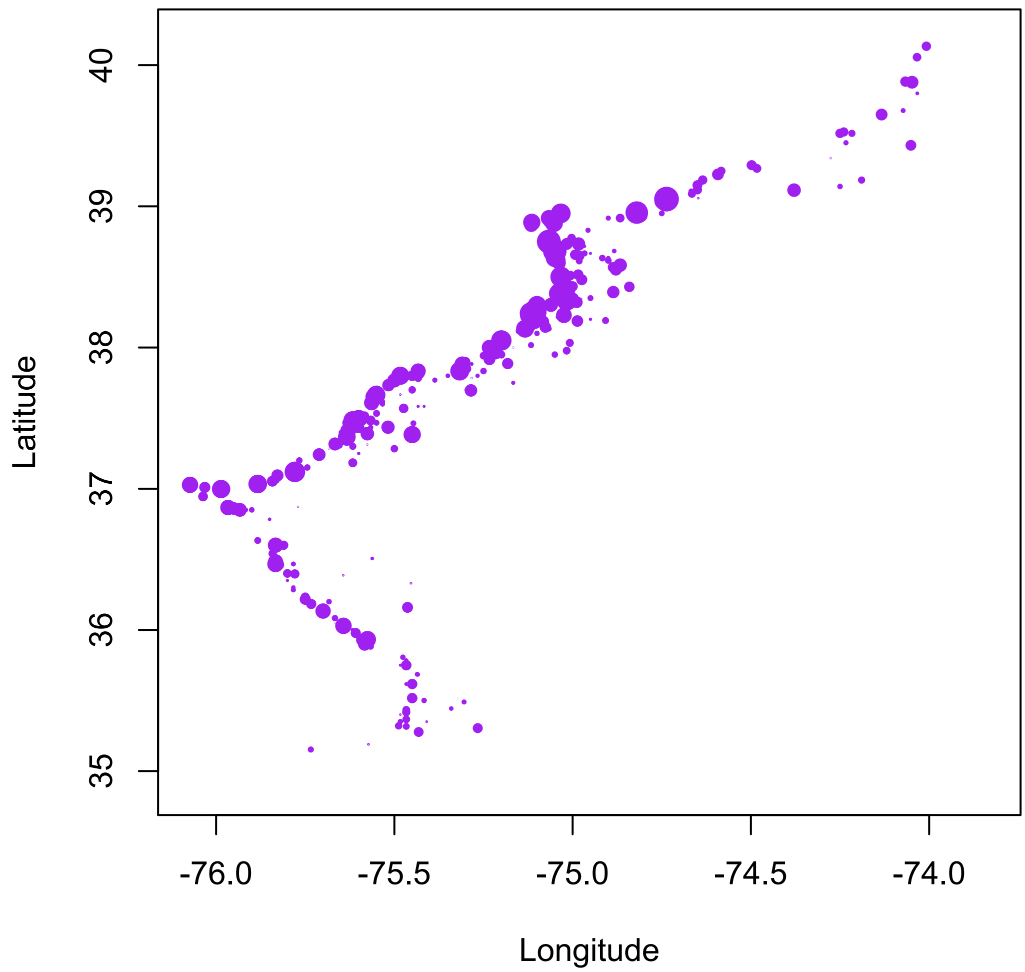

Figure 3.3. Raw catch rate distribution map for NMFS survey data. Quadrate size is proportional to the value of the mean catch rate

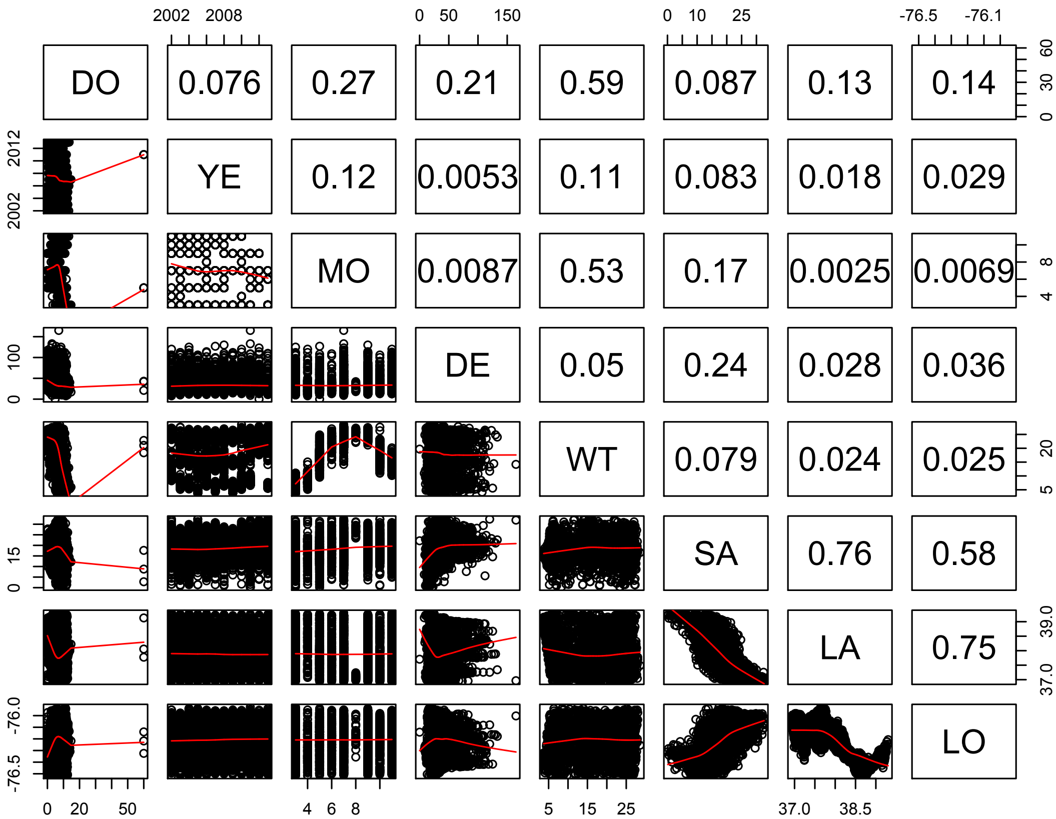

Figure 3.4. Pairwise scatter plots and Spearman correlation coefficients between explanatory variables based on CHESMMAP survey data. Abbreviations are as follows: DO=dissolved oxygen, YE=year, MO=month, DE=depth, WT=water temperature, SA=salinity, LA=latitude, LO=longitude.

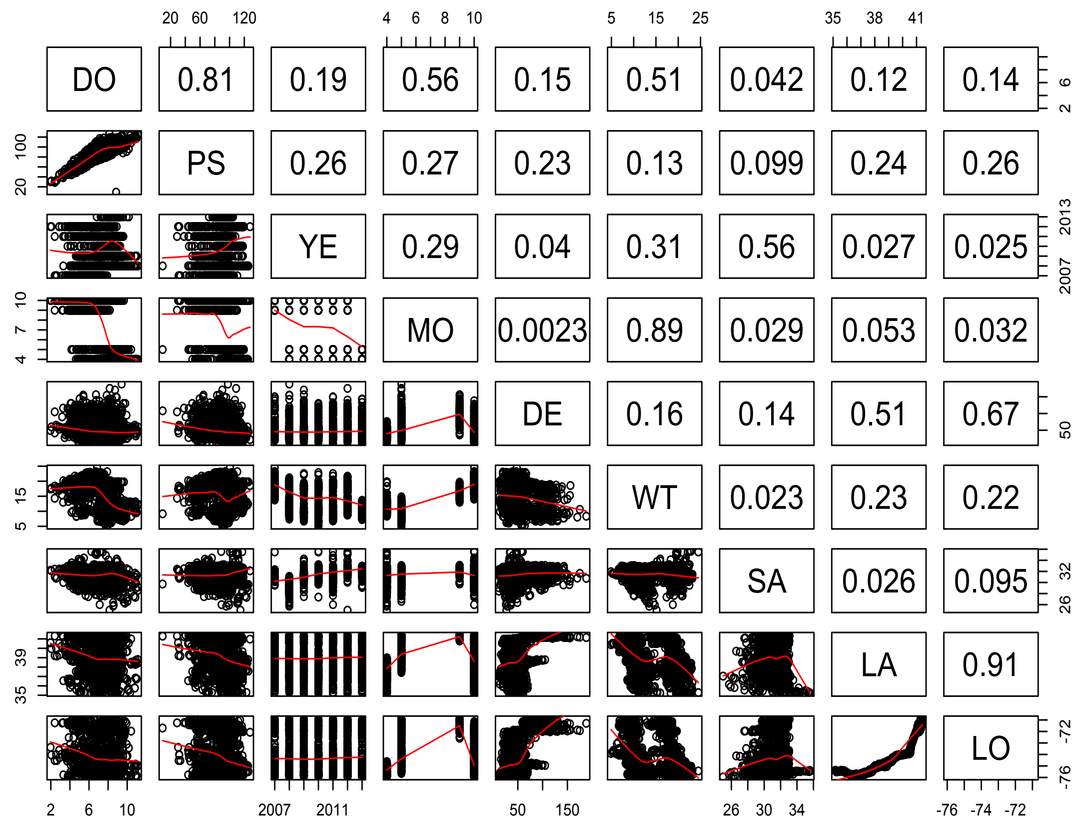

Figure 3.5. Pairwise scatter plots and Pearson correlation coefficients between explanatory variables based on NEAMAP survey data. Abbreviations are as follows: DO=dissolved oxygen, PS=percentage of oxygen saturation, YE=year, MO=month, DE=depth, WT=water temperature, SA=salinity, LA=latitude, LO=longitude.

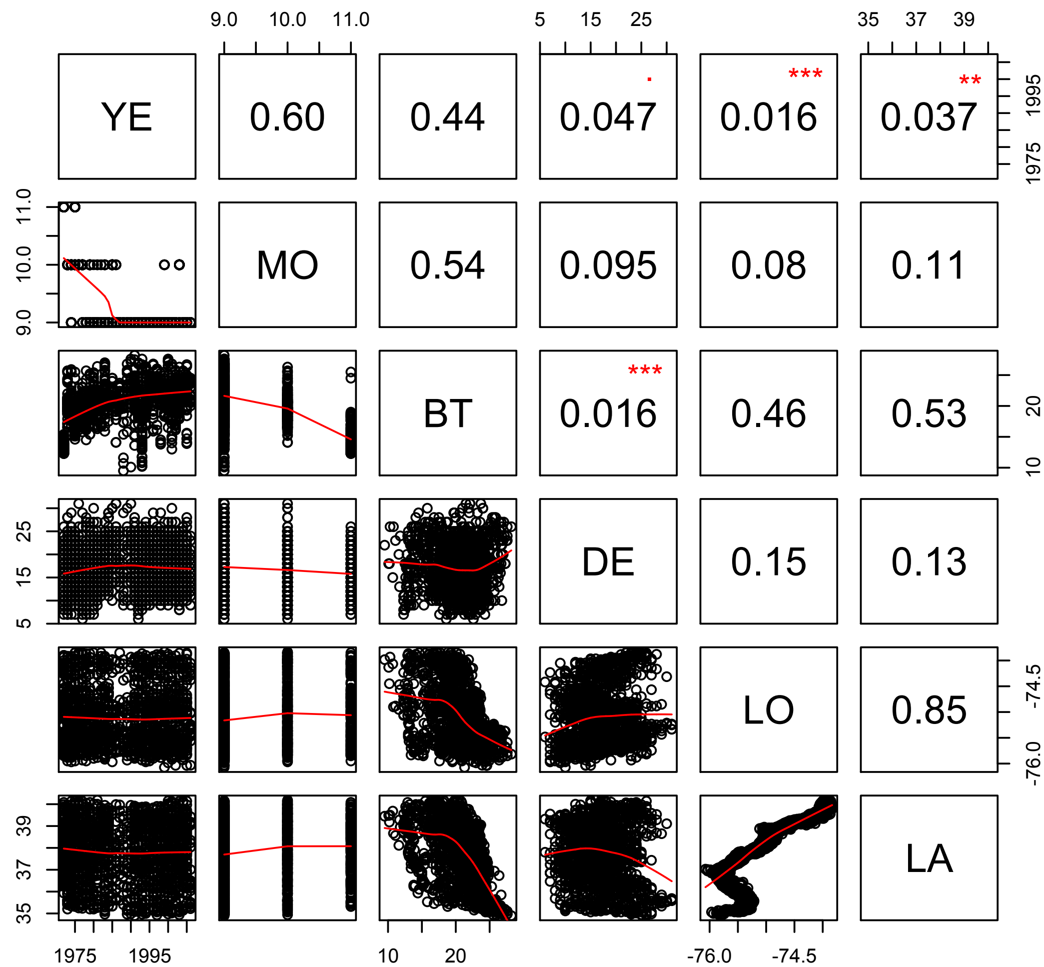

Figure 3.6. Pairwise scatter plots and Pearson correlation coefficients between explanatory variables based on NMFS survey data. Abbreviations are as follows: DO=dissolved oxygen, PS=percentage of oxygen saturation, YE=year, MO=month, BT=bottom temperature, DE=depth, LA=latitude, LO=longitude.

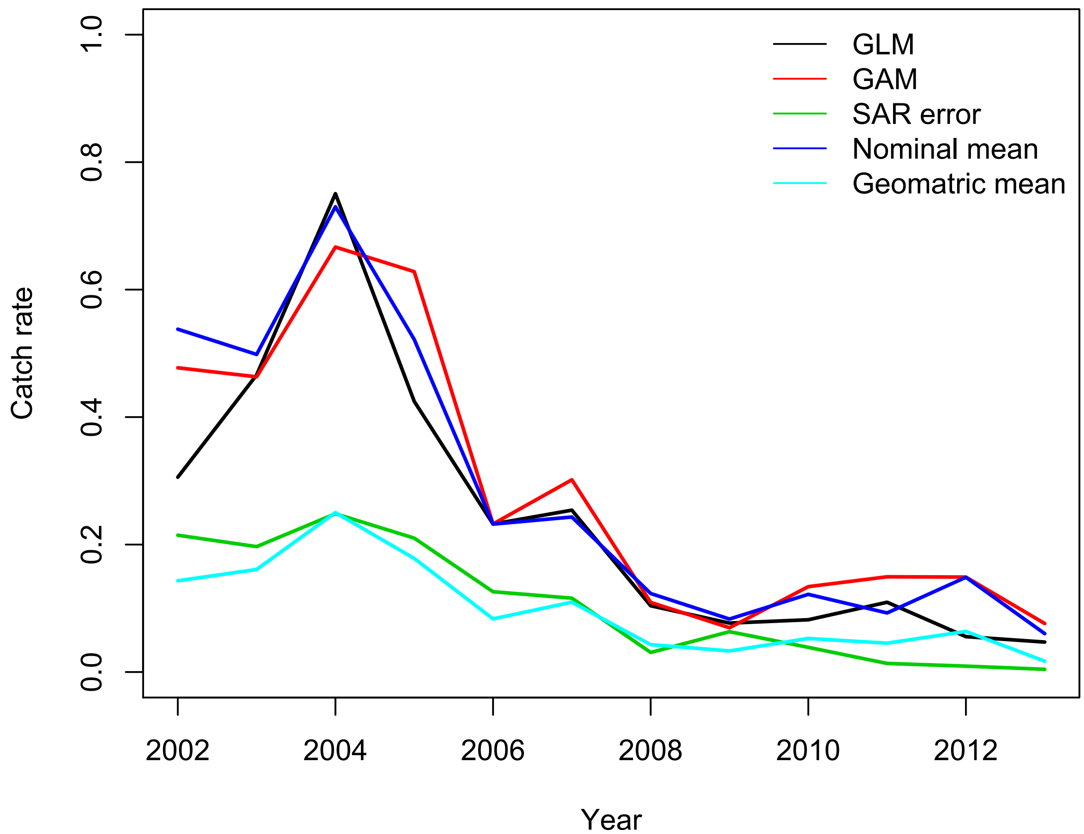

Figure 3.7. Trend of standardized catch rate over time generated by three delta models (i.e. Delta GLM, Delta GAM, Delta SAR error model) and nominal mean and geometric mean for CHESMMAP.

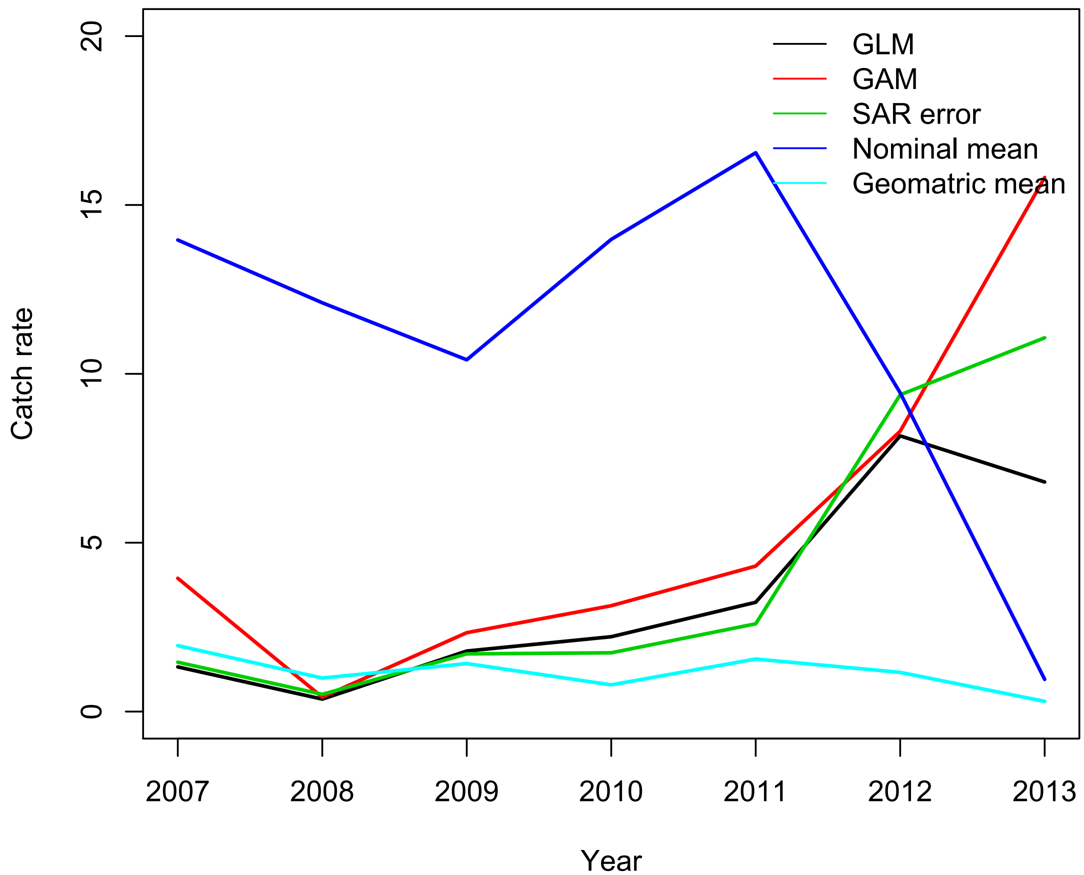

Figure 3.8. Trend of standardized catch rate over time generated by three delta models (i.e. Delta GLM, Delta GAM, Delta SAR error model) and nominal mean and geometric mean for NEAMAP.

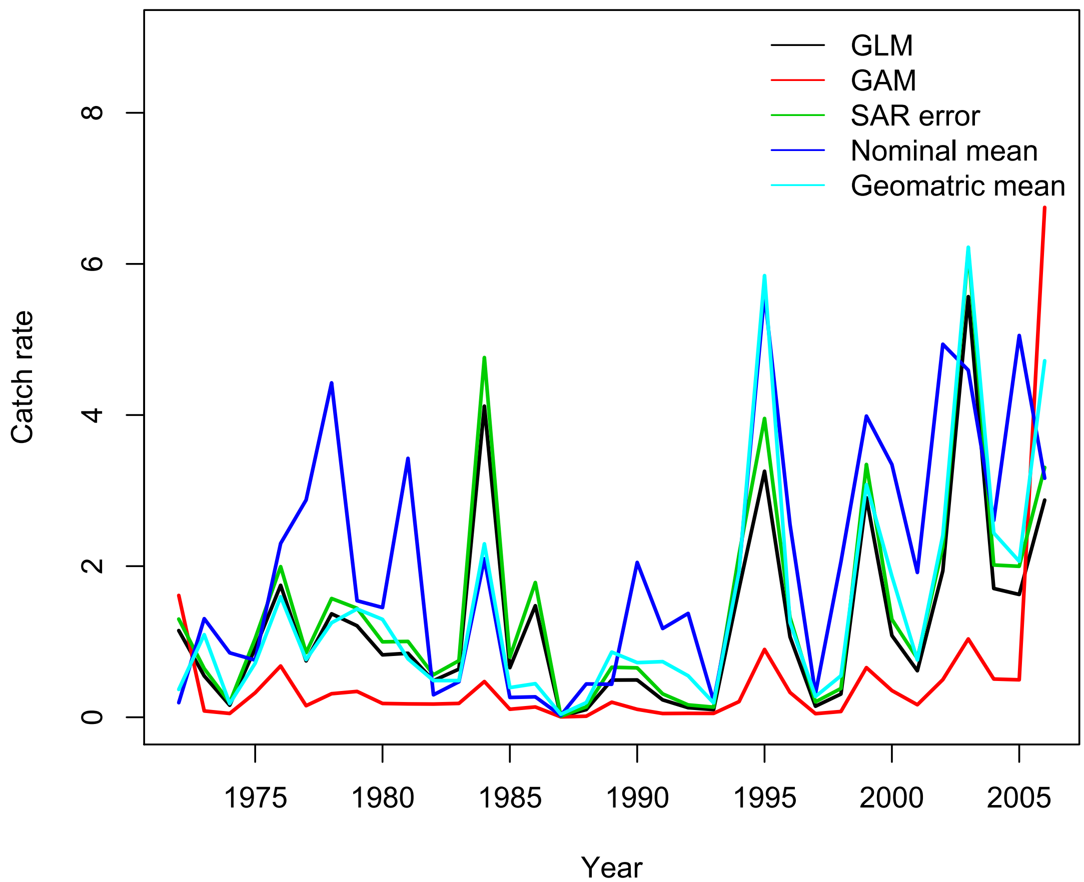

Figure 3.9. Trend of standardized catch rate over time generated by three delta models (i.e. Delta GLM, Delta GAM, Delta SAR error model) and nominal mean and geometric mean for NMFS.

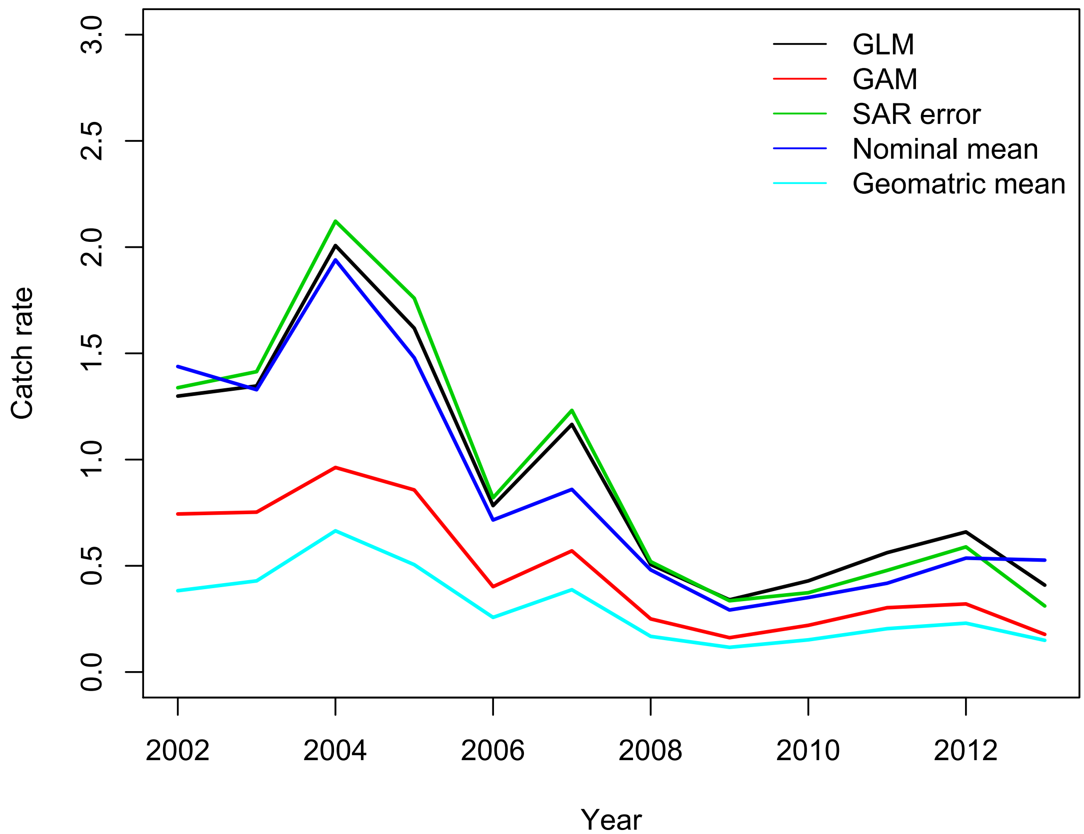

Figure 3.10. Trend of standardized positive catch over time generated by three delta models (i.e. Delta GLM, Delta GAM, Delta SAR error model) and nominal mean and geometric mean for CHESMMAP.

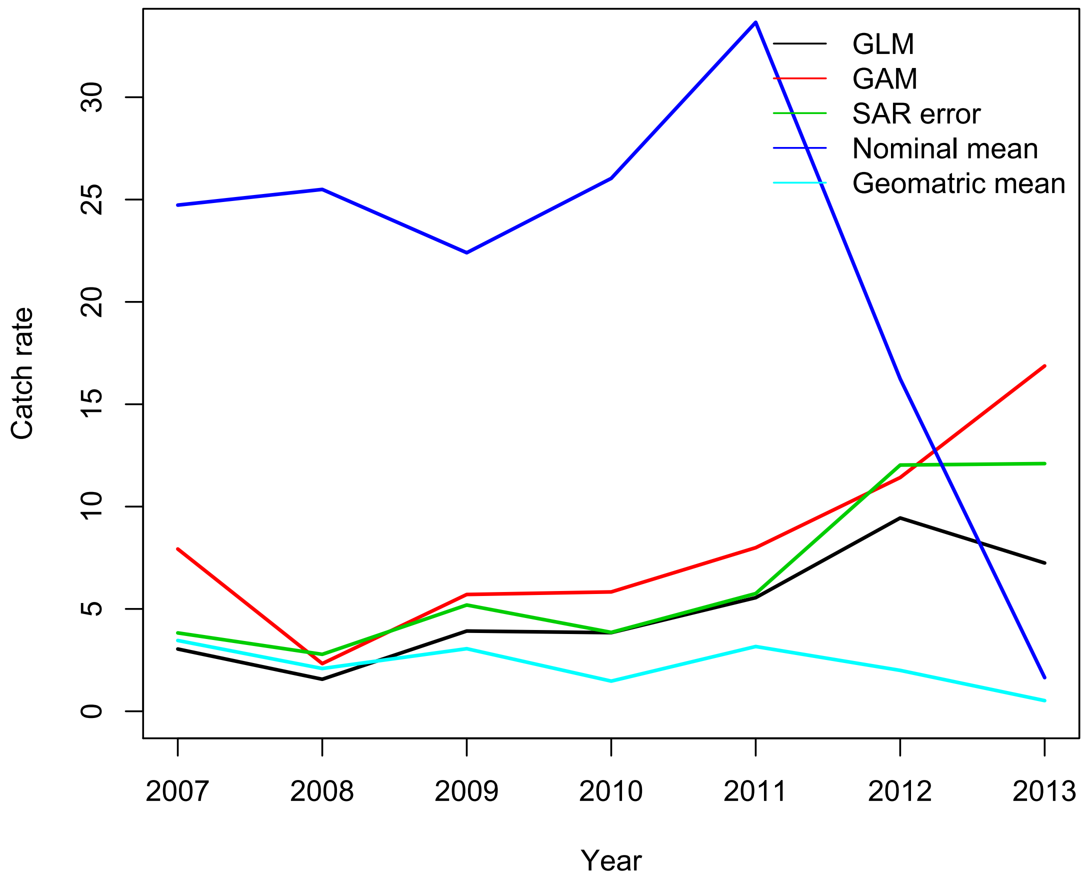

Figure 3.11. Trend of standardized positive catch over time generated by three delta models (i.e. Delta GLM, Delta GAM, Delta SAR error model) and nominal mean and geometric mean for NEAMAP.

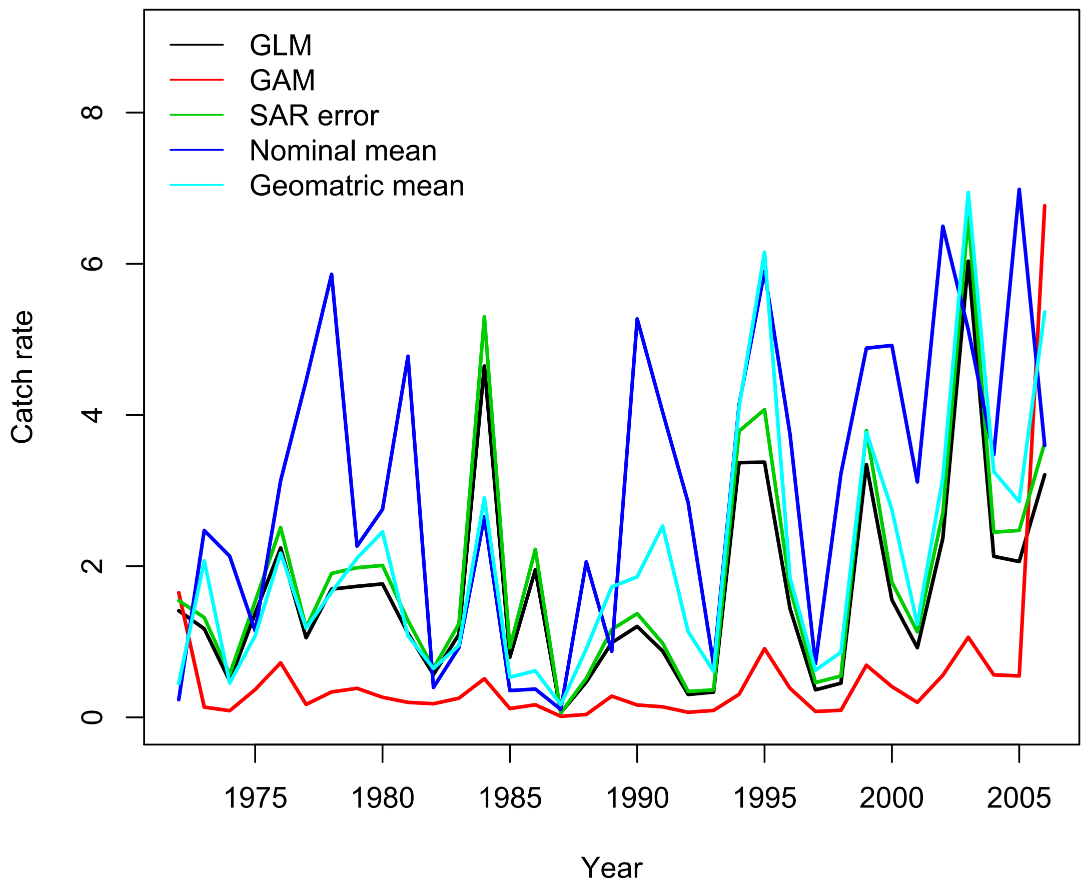

Figure 3.12. Trend of standardized positive catch over time generated by three delta models (i.e. Delta GLM, Delta GAM, Delta SAR error model) and nominal mean and geometric mean for NMFS.

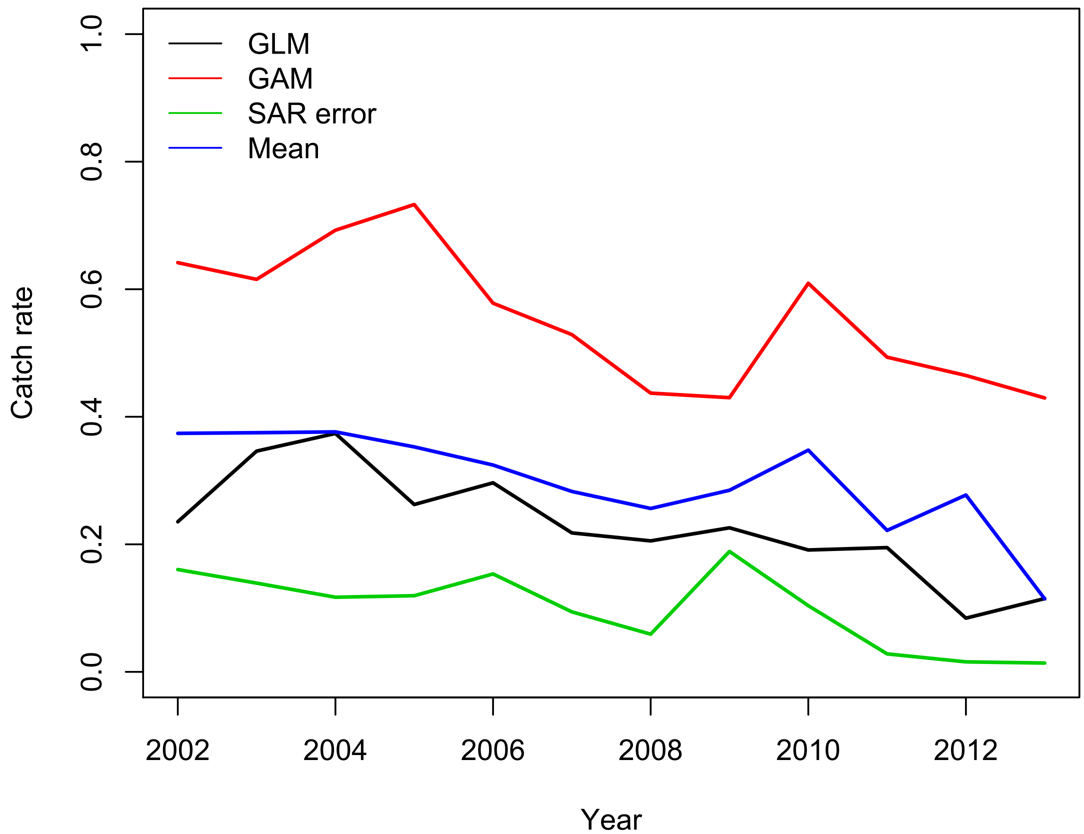

Figure 3.13. Trend of catch probability over time generated by three delta models (i.e. Delta GLM, Delta GAM, Delta SAR error model) and nominal mean for CHESMMAP.

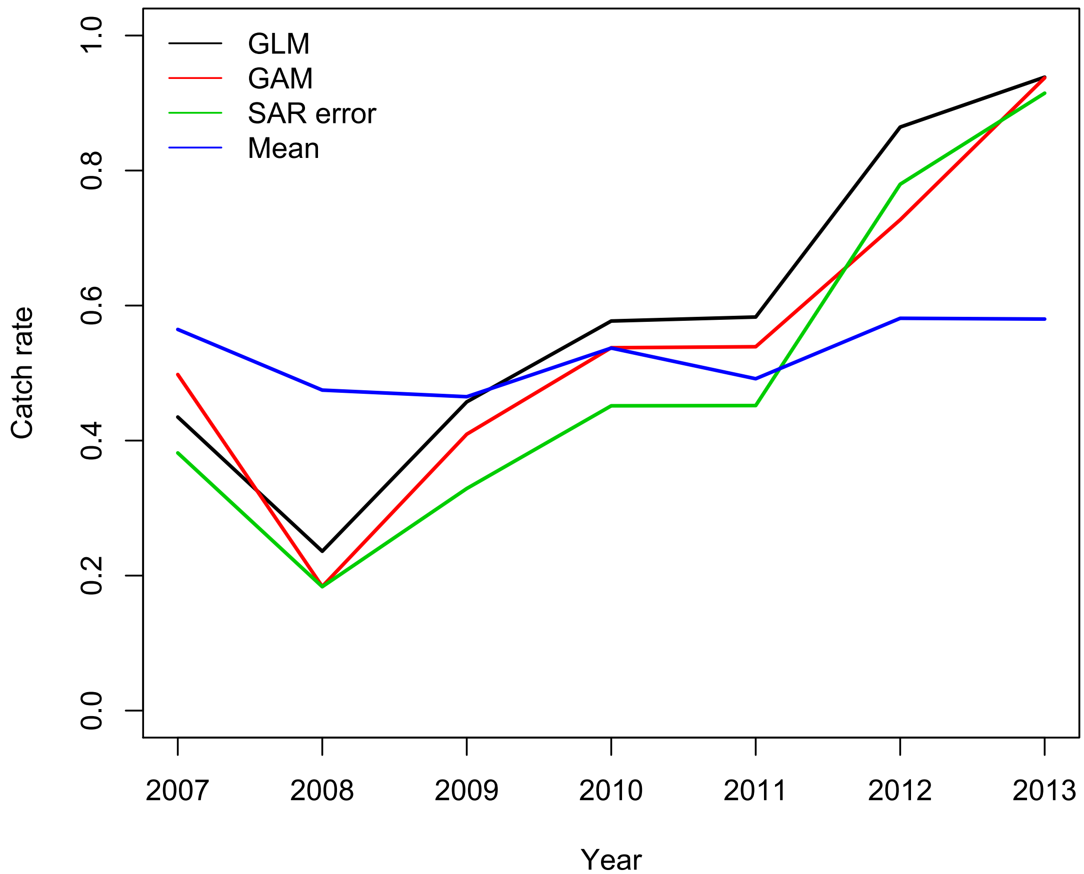

Figure 3.14. Trend of catch probability over time generated by three delta models (i.e. Delta GLM, Delta GAM, Delta SAR error model) and nominal mean for NEAMAP.

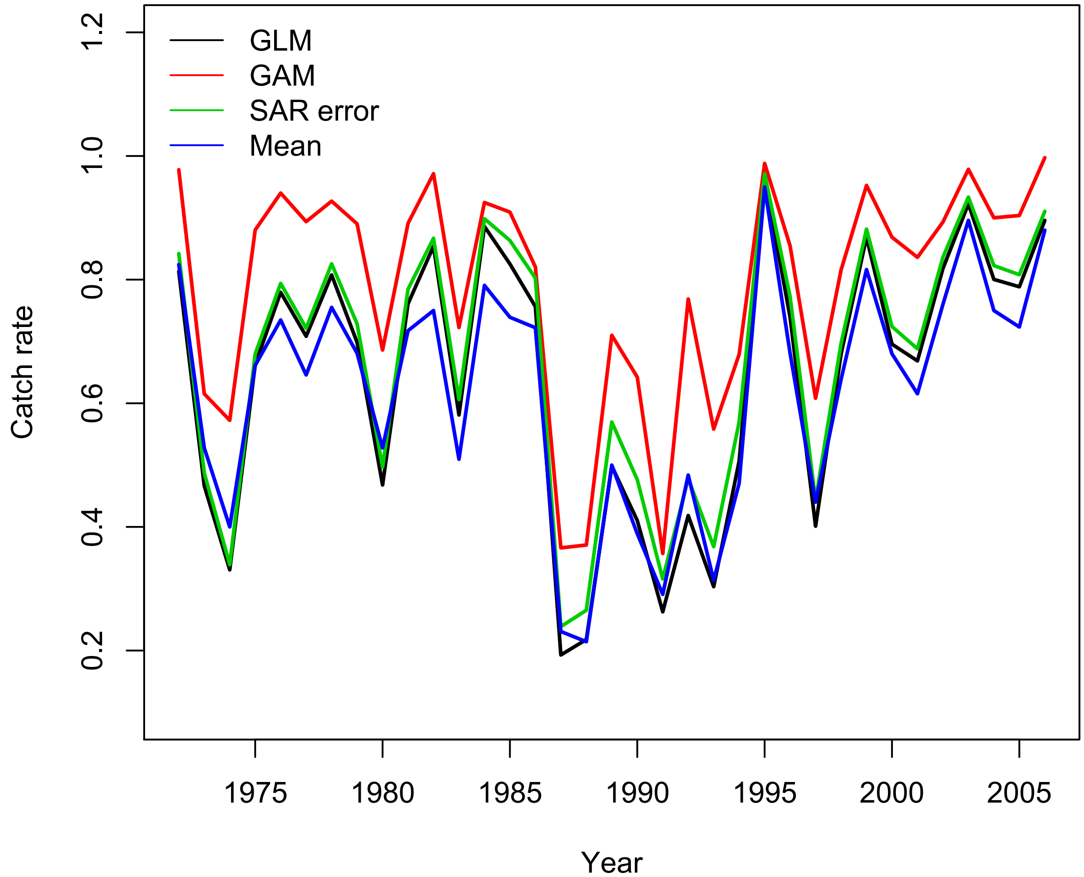

Figure 3.15. Trend of catch probability over time generated by three delta models (i.e. Delta GLM, Delta GAM, Delta SAR error model) and nominal mean for NMFS.

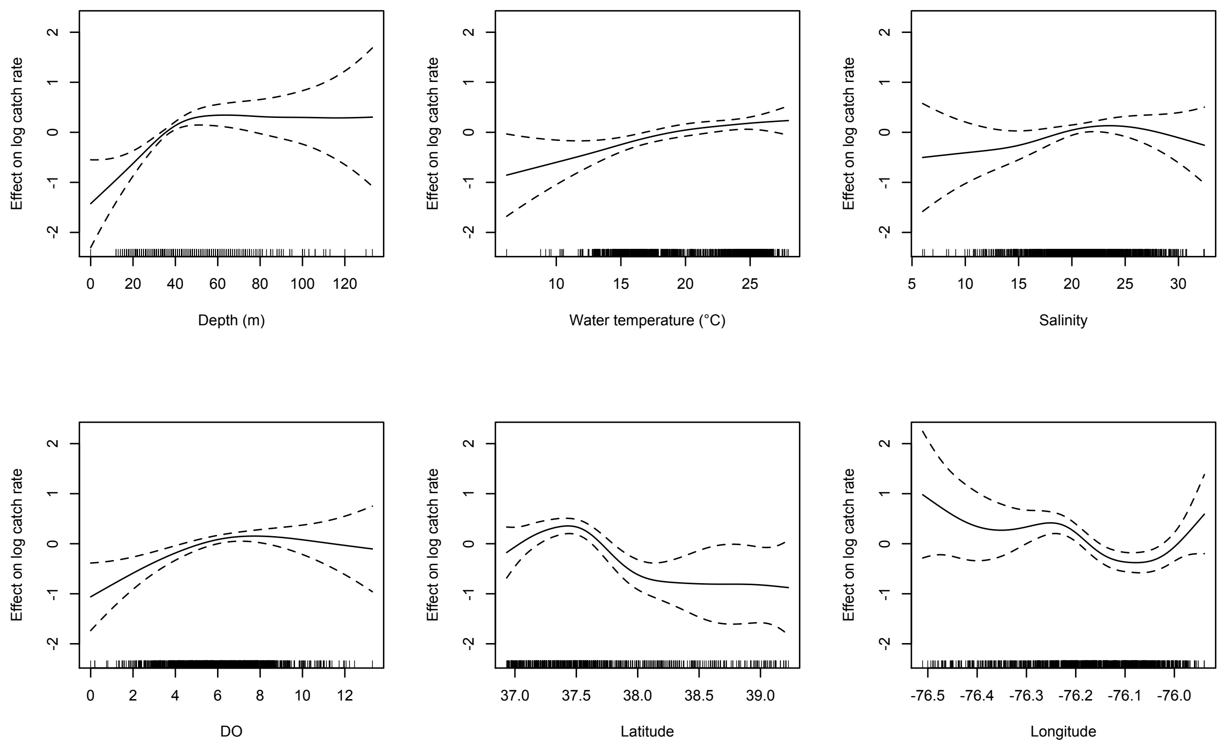

Figure 3.16. CHESMMAP survey: Effect of depth, water temperature, salinity, dissolved oxygen, latitude, and longitude on log catch rate. Dotted lines around the trend line represent the 95% confidence intervals.

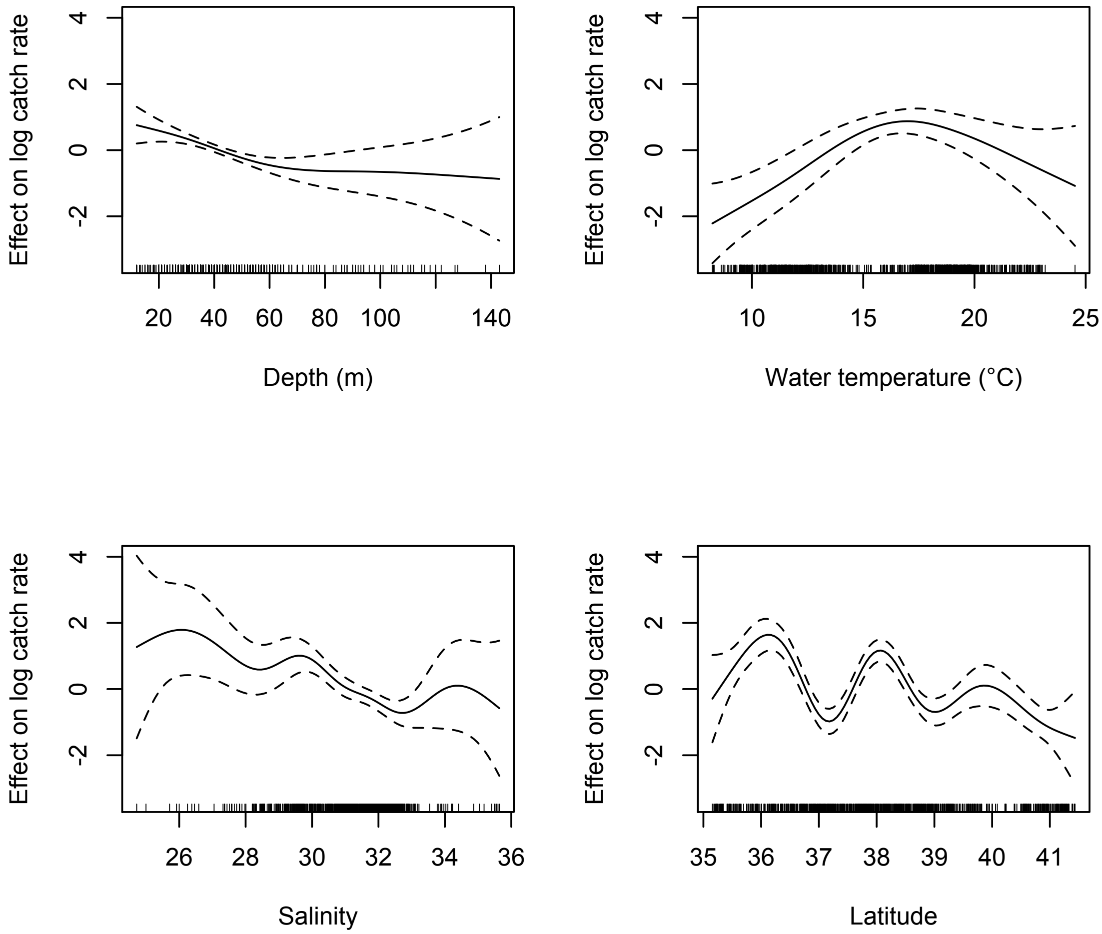

Figure 3.17. NEAMAP survey: Effect of depth, water temperature, salinity, and latitude on log catch rate. Dotted lines around the trend line represent the 95% confidence intervals.

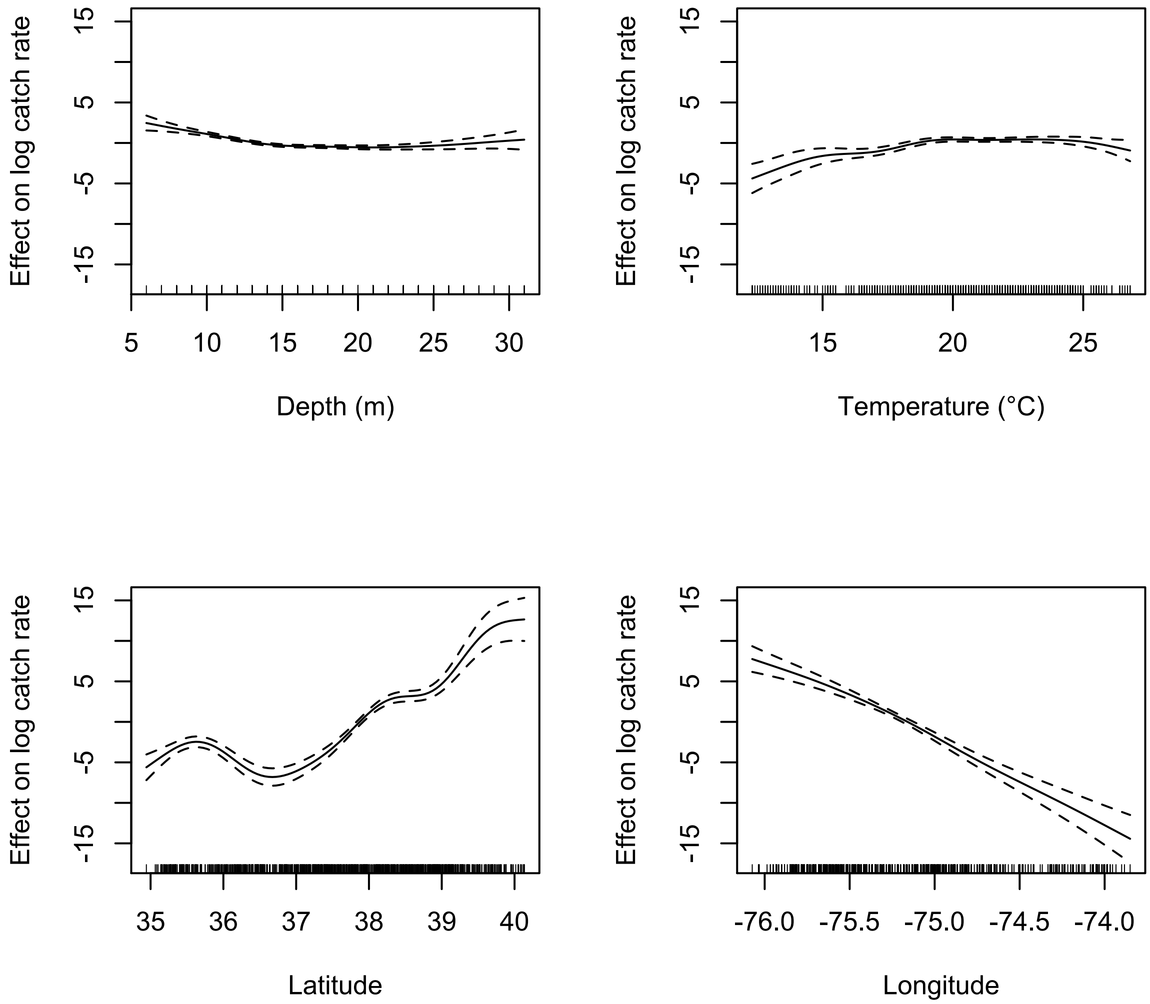

Figure 3.18. NMFS survey: Effect of depth, temperature, latitude, and longitude on log catch rate. Dotted lines around the trend line represent the 95% confidence intervals.

Chapter 4

Influence of nonstationary process on management strategy evaluation: An example based on Atlantic Weakfish along western Atlantic Ocean

4.1 Abstract

Management strategy evaluation (MSE) is a simulation-based process for comparing a series of alternative management strategies and assessing the consequence of each strategy under alternative management objectives in a virtual world. MSE process usually contains 1) an operating model to generate future data and estimate parameters, 2) an estimation model to assess the stock, 3) a decision rule to evaluate each management strategy. The MSE was used in this analysis to evaluate the management strategies for Atlantic Weakfish, *Cynoscion regalis*, in western Atlantic Ocean. The stock-recruitment relationship was explored at first, and the best two stock-recruitment models, Ricker and Beverton-Holt models, were selected into the next simulation process. The results of the analysis indicate that the current F-based management strategy for Weakfish appears to meet the management sustainability goals when the actual resource dynamics are consistent with the current stock assessment and for two scenarios with alternative stock-recruitment relationships. However the appropriateness of the biomass-based reference point used to evaluate probability of the population being lower than the reference point depends on the stock assessment models selected. The current biomass-based reference point tends to be high if the true population dynamics has nonstationary natural mortality.

4.2 Introduction

Management strategy evaluation (MSE) is a simulation-based process of comparing a series of alternative management strategies and assessing the consequence of each strategy under several management objectives in a virtual world. MSE also includes the process of designing and testing management procedures (MPs), which are reasonable for the objective to meet. Instead of achieving an optimal strategy or decision, its goal is to provide fisheries managers information to make feasible policies which are robust to uncertainties and errors in natural system. The impact of uncertainties and errors in fisheries stock assessment has resulted in the development of biologically risk-diminishing tasks that account for scientific uncertainties about fish stock status and alternative management approaches (Jiao et al., 2005; Shertzer et al., 2008). The advantages of MSE over other kinds of approaches are that it enables the stakeholder to participate in developing management plans. In addition, MSE allows researchers and managers to test the involvement of uncertainties and errors when implementing various management actions.

The results of an MSE are performance measures that quantify the extent to which a management strategy is able to satisfy the (often conflicting) management goals (Kell et al., 2006). In addition, the results of an MSE can be used to determine how well estimation models are able to estimate quantities (such as current biomass) that are of interest to management. MSE has been used to evaluate current and alternative management strategies for many fisheries worldwide, including those for South African sardine and anchovy (De Oliveira et al., 1998, De Oliveira and Butterworth 2004), prawns off northern Australia (Dichmont et al., 2006), species in Australia's South East multispecies fishery (Punt et al., 2002), krill off Antarctica (Constable 2005), and flatfish in the Northeast Atlantic (Kell et al., 2005).

High annual recruitment variation is an important component in fish stock management. Management strategies should be designed to take the uncertainties of fish populations and their assessments into account. Uncertainties in fishery mainly include estimation uncertainties and future process uncertainties. Estimation uncertainties refer to all uncertainties about the model structure and the associated parameters. Future uncertainties means how processes may change in the future has nothing to do with how well we have estimated them in the past. Here, recruitment variation is a form of future uncertainty, which can be a significant component of the total uncertainties, particularly when a large proportion of the total population consists of the recruiting year class. Fish populations with different levels of recruitment variability have different risk of extinction and recovery. One method to control uncertainty from recruitment variation is to assume that future recruitment will occur with a similar distribution and time-series structure to historical recruitment (Maunder and Deriso, 2003). Therefore, it is important to have good estimates of historic recruitment variability when modelling spawning-recruitment relationship.

The use of stationary model has been ubiquitous in traditional population dynamics and stock assessment models due to the difficulties in solving nonstationary population dynamics models (Jiao et al., 2010). In recent years, nonstationary processes have been investigated both theoretically and practically in ecological studies (Priestley, 1988; Fu et al., 2001; Turchin, 2003). However, they have seldom been utilized in current fisheries modelling and stock assessments, especially when age-structured models are used (Jiao et al., 2009; 2012).

Nonstationary population processes will arise when there are changes in the natural environment, lack of population regulations, and growth to potential equilibrium (Royama, 1992). In addition, uncertainties in model selection are higher when a model is directly selected without evaluation with other possible models, particularly those that are nonstationary process model.

The Weakfish here is used as an example to explore the "best" model, which were used in MSE process. The nonstationary process is assigned to the value of natural mortality (M), one of the most uncertain and dominant parameters in fisheries assessment (Vetter, 1988; Clark, 1999). Like other fish species, the value of M of Weakfish is considered as a nonestimable parameter inside of the SCA models, and is assumed to be known (M=0.25) when traditional population assessment models are used (ASMFC, 2006; NDPSWG, 2009; NEFSC, 2009). However, recent work indicates that the M value for Weakfish is not constant, and the ASMFC Weakfish Stock Assessment Subcommittee has been working on how to estimate it (ASMFC, 2006; NEFSC, 2009). Fortunately, Jiao et al., (2012) have worked out a way in estimating M through a nonstationary process, and were also based on Atlantic Weakfish. In this study, I explored the "best" operating model on stock-recruitment relationships based on both a stationary and a nonstationary SCA model (Jiao et al., 2009; 2012). I also explored the F-based management strategies in managing the Weakfish population based on measurement of risk of overfishing ($F>F_{ref}$; F_{ref} is the F-based reference point) and being overfished ($SSB<SSB_{ref}$; SSB_{ref} is the SSB-based reference point).

4.3 Method

4.3.1 Data Resource

The simulation study is based on the Atlantic Weakfish stock assessment results (Jiao et al., 2012). Biological reference points are from the current Weakfish fisheries management references points (NEFSC 2009).

4.3.2 Stock Recruitment Model

Due to the high variation and uncertainties in recruitment and spawning stock relationship, five commonly used stock-recruitment models were utilized to compare the relationship between recruitment and spawning stock biomass. Inaddition, the environmental factors (such as climate changes or decadal oscillation) that influence recruitment dynamics were considered also based on the four biological samples:

Beverton-Holt model: $R = \frac{\alpha S}{1+\beta S} e^{\varepsilon_{R_1}}$ (1)

Ricker model: $R = Se^{\alpha-\beta S}e^{\varepsilon_{R_2}}$ (2)

Cushing model: $R = \alpha S^{\beta}e^{\varepsilon_{R_3}}$ (3)

Gamma model: $R = \alpha S^{\gamma}e^{-\beta S}e^{\varepsilon_{R_4}}$ (4)

Shepherd: $R = \frac{\alpha S}{1+\beta S^{\gamma}}e^{\varepsilon_{R_5}}$ (5)

where R is the recruitment of the stock, S is the spawning stock biomass, α and β are parameters in the model. The random error in each model follows a normal distribution ($\varepsilon_{R_i} \sim (0, \sigma_{R_i}^2)$). Akaike's information Criterion (AIC) was used to compare model goodness-of-fit and select SR models.

4.3.3 Statistical Catch-at-Age Model

Two age-structured models were conducted to represent the dynamics of the Weakfish population (Jiao et al., 2012), with two different assumptions for natural mortality (M). The first model is a stationary statistical catch-at-age (SCA) model with constant natural mortality. The second one is a nonstationary SCA model with time-varying natural mortality, following a random-walk process.

$$\ln(M_y) = \ln(M_{y-1}) + \varepsilon_M$$

$$\ln(M_{y-1}) = \ln(\bar{M}) + \varepsilon_M$$

$$\bar{M} \sim U(b_1, b_2)$$

where M_y is M at year y and M_y follows a random-walk process. These two models contain four submodels, including (i) an abundance-age model to describe the dynamics of the population, (ii) an observation model to describe the relationship between the estimated catch and observed catch in the fishery, (iii) a series of observation models to describe the relationship between stock abundance and relative abundance indices from the fishery or fishery-independent surveys, and (iv) an M submodel if M was assumed as unknown.

The statistical catch-at-age model used to generate assessment data can be written following Jiao et al., (2011):

$$\ln(N_{a+1,y+1}) = \ln(N_{a,y}e^{-(M+S_a\square_y)}) \quad 1 \leq a \leq 6$$

$$\ln(N_{a+1,y+1}) = \ln(N_{a-1,y}e^{-(M+S_aF_y)} + N_{a,y}e^{-(M+S_aF_y)}) \quad a=6^+$$

$$\ln(C_{a,y}) = \frac{F_{a,y}}{F_{a,y}+M}N_{a,y}(1-e^{-(M+F_{a,y})} + \varepsilon_C$$

$$F_{a,y} = F_yS_a$$

$$I_{a,y} = q_a N_{a,y}$$

$$\ln(R_y) = \ln(\bar{R}) + \varepsilon_y$$

$$\ln(R_y) = f(SSB_{y-1}) + \varepsilon_R$$

$$SSB_y = \sum_a N_a W_{a,y}$$

$$\ln\,(N_{a=1,y=1982}) = \ln\,(\widehat{N_{a=1,y-1982}}) + \varepsilon_N$$

$$\widehat{N_{a=1,y-1982}} \sim U(1{,}100) * \varepsilon_N$$

$$M = known\ constant\ or\ unknown$$

where a is age, y is year, and r is age at recruitment. $N_{a,y}$ is the population abundance of age a fish in year y, $C_{a,y}$ is the catch of age a fish in year y, $F_{a,y}$ is the fishing mortality rate of age a fish in year y, S_a is the fishing selectivity of age a fish, R_y is the recruitment in year y $I_{a,y}$ is the abundance index for age a fish in year y and q_a is the catchability coefficient of age a, and M is supposed to be known and fixed at 0.25 for all age groups and years (ASMFC, 2006; NEFSC, 2009). A constant vector was used to model selectivity instead of a logistic curve, because several types of catch composition and are contained in catch-at-age matrix, which lead to less regular selectivity.

Recruitment is defined as the number of age-1 Weakfish entering the stock. When recruitment (R) model is integrated outside of SCA model, the recruitment in year y (R_y) is assumed to be estimated and follow the distribution of $\ln(R_y) = \ln(\bar{R}) + \varepsilon_y$. On the other hand, when R is modelled by a stock-recruitment curve, such as Cushing and Beverton-Holt (Ricker, 1975; Quinn and Deriso, 1999), R model is integrated inside of SCA model, becoming a submodel of SCA model:

$$\ln(R_y) = f(SSB_{y-1}) + \varepsilon_R$$

$$SSB_y = \sum_a N_{a,y} W_{a,y}$$

Therefore, there were four models to be compared here: (i) M1: a stationary SCA with Ricker model; (ii) M2: a stationary SCA with Beverton-Holt model; (iii) M3: a nonstationary SCA with Ricker model; (iv) M4: a nonstationary SCA with Beverton-Holt model.

4.3.4 MSE process though simulations to compare MSE recommendation from 4 models

The resulting 4 SCA models were then be used to project a number of simulations for future population dynamics and Weakfish management, which is known as MSE. Management measures that were used to evaluate the performance of each management strategy include quota in the next 30 years, risk of overfishing the fishery and risk of the population being overfished, population size over time and quota stability etc. Management strategy or solution were mainly based on fishing mortality and annual quota.

Amendment 4 recommend the fishing mortality target for Weakfish be $F_{target} = F_{30\%} = 0.31$, $F_{threshold} = F_{20\%} = 0.5$ (48th SAW Assessment Report, 2009), which is an overfishing definition. Fifteen thousand iterations were carried out for each of five different target fishing mortalities ($F_{target} = 0, 0.1, 0.31, 0.5, 1$) with each simulation running for 30 years into the future. Each F_{target} was evaluated in terms of the number of years in each simulation in which spawning-stock biomass B is below biomass reference points $SSB_{threshold} = SSB_{20\%} = 31.8$ million pounds.

The following simulation algorithm was used (also see flowchart Figure 4.1): (i) historical assessment data were read in, since the parameters, such as mortality, and abundance directly, have been estimated from the stock assessment models, I generated recruitment based on the "best" SR model; (ii) in the first year, fishing mortality (F) is assumed to be equal to a three-year historical average: in subsequent simulation years, F is determined by application of management decisions from previous years with implementation error; (iii) a stock assessment and associated short-term forecast were carried out, based on data up to the current year; (iv) a management decision for the following year was then determined by using information from the assessment and forecast and following the specified management plan to generate an intended landings yield. Steps (ii) – (iv) are repeated for 15000 simulations for each scenario, and each simulation involved projecting the simulated stock forward for 30 years.

4.3.5 Risk assessment

Risk assessments were used to estimate the probability that a particular event would occur within a specified time given specified management strategies. Management measures including quota in the next 30 years, risk of overfishing the fishery, risk of the population being overfished, population size over time and quota stability, were assessed as the probability that the Weakfish stock will decrease over time. I also estimated the probability that the population growth rate is less than one, and the probability that the population size after t years is less than the current population size.

4.4 Result

Five stock-recruitment models were fitted based on the posterior distribution obtained by Jiao et al., (2010). The models then were compared by AIC, and Ricker model, Beverton-Holt model, and Cushing model were the best three models. I randomly selected 16 iterations out of 15,000, and plotted them based on these three models (Figure 4.2). From Figure 4.2, we can see that, some patterns from Cushing model were less reasonable regardless of whatever AIC values were close to Ricker model and Beverton-Holt model. Thus, Ricker model and Beverton-Holt model were selected to be used for the following simulation steps.

The corresponding population size and population growth rate and TACs over time given different F levels were shown in Figure 4.3. Since the selection of recruitment model as well as SCA is of high uncertainty, results of using 2 types of recruitment models and 2 types of SCA models were shown in Figure 4.3. All four types of combined models (i.e., B-H model combined with stationary SCA model, Ricker model combined with stationary SCA model, B-H model combined with non-stationary SCA model, Ricker model combined with non-stationary SCA model) implied that the population would reach equilibrium over time under different F levels because of the assumption of the density-dependent stock recruitment relationships.

However, the population size and the population growth rate and the TACs simulated by the 4 types of combined models were different as shown in Figure 4.3. Model M1 yielded the largest population size as well as largest TAC among the four combined models, while model M3 yielded the smallest amount of population size and model M4 yielded the smallest amount of TAC in the simulation. Specifically, model M1 under the F was 1 resulted in the largest amount of the TAC.

Model M1 took the longest time to become stable in simulating population size and population growth rate in the 'future'. The population growth rate under M3 for F was 1 oscillated at the beginning, and became equilibrium later. M1 yielded extremely large population size under $F = 0$. The variation of population size decreased while the uncertainty of TAC increased with the fishing mortality increased.

The risk shown as probabilities higher or lower than 31.8 million pounds of spawning stock biomass (SSB) indicated the risk of the population being overfished or not (Figure 4.4).

The probability of a SSB lower than 31.5 million pound was always high when *F* was 1 for all four models (Figure 4.4). For the two stationary models, model M1 and M2, the SSB lower than 31.5 million pound for *F* equal 0, 0.1, 0.31 were always low. Whereas, for the two non-stationary models, model M3 and M4, the SSB lower than 31.5 million pound were high even for *F* equal 0.1, 0.31 and 0.5. For model M3, the SSB lower than 31.5 million pound were approximately equal to 0.4 even the *F* was 0.

4.5 Discussion

The current management strategy for Weakfish as to whether it achieved the management sustainability goals depend on the stock assessment models to be believed. Although this result was anticipated when this whole analysis was originated, it is not permanently assured that all management strategy would perform as expected even under relatively ideal circumstances. For instance, Kell et al., (2005) conducted an MSE study on North Sea cod based on the harvest control rule used by the International Council for the Exploration of the Sea (ICES). However, the results of this MSE showed that the management strategies did not perform very well. Therefore, this management strategy evaluation only dealt with the current management strategies for Weakfish, and was evaluated whether it is robust to a series of uncertainties. Additional work is also needed to evaluate whether other management strategies would improve performance in achieving management goals and objectives.

Modeling recruitment is of importance for future management strategy evaluation, since the relationship of stock-recruitment is fundamental for fish stock assessment and management (Ricker, 1975; Hilborn and Walters, 1992 The selection of stock-recruitment model is perhaps one of the most difficult task in fisheries not only because of the variation in recruitment and large measurement error in spawning stock size (Hilborn and Walters, 1992) but also result from the uncertainties in applying the SR relationship is caused by choosing a particular form of SR curves to fit the stock-recruitment data (Wang and Liu, 2004).

There are many ways to select a suitable stock-recruitment model based on the SR data. The equations could be considered as an empirical description but not an explanation. The relationship between spawning stock and recruitment should be based on the biological details and life history (Wang and Liu, 2004). The recruitment of Weakfish is currently explained by Ricker model. However, it is still beneficial if other spawning-recruitment model is also considered when conducting simulation studies.

The analyses of this paper were based on fitting both the stock-recruitment models and SCA models to the actual data and quantifying parameter uncertainty using samples from a Bayesian posterior distribution simulations based on samples from the posterior distribution provide possibility convenient tool that can be used for risk assessment directly.

The natural mortality rate used in this analysis, was 0.25 for the 2 stationary SCA models, while a posterior distribution of left skewed curve with mean of 0.83 was used for the 2 non-stationary SCA models. The natural mortality has been recognized to be increasing in the past 30 years due to some unknown reasons. Thus, it is possible that the natural mortality rate will remain high in the near future. Thus, the results from the 2 non-stationary models might be more useful since the natural mortality is unlikely to be that small (0.25) any more.

The future work should be exploring the robustness of the management strategy to the effects of violations of the basic assumptions of the operating model on which this paper is based. The major uncertainties that need to be considered are the nonstationary effects related to the ecosystem variability, predator-prey relationship, and climate changes. It is not fully explored how changes in the age composition and abundance of the Weakfish population have led to changes in life history changes, such as maturity, growth, as well as distribution and migration. Finally, the difference between TACs and subsequent landings could also be taken into account in future possible adaptive management strategies to avoid uncertainty caused by selecting appropriate operating models which may be nonstationary.

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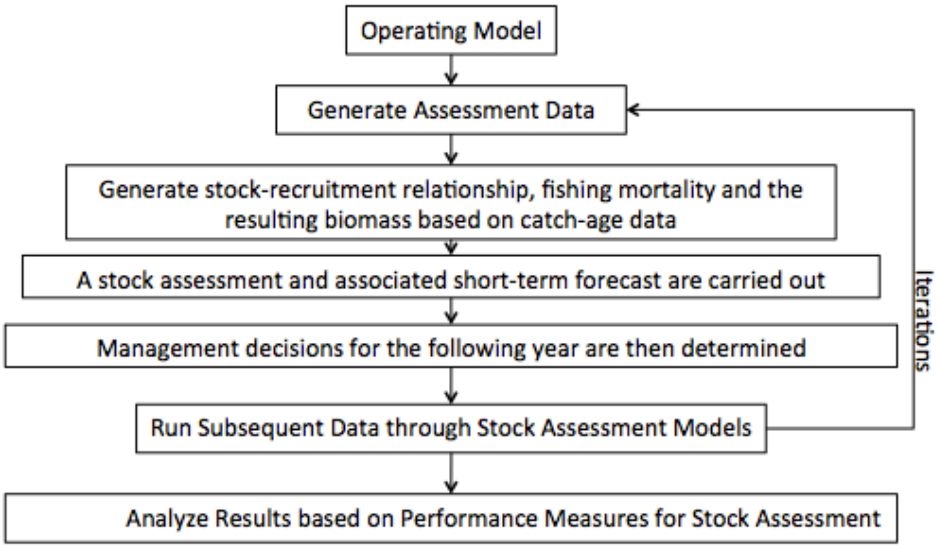


Figure 4.1. A diagram of the proposed simulation study to investigate the influence of model selection in fisheries stock assessment.

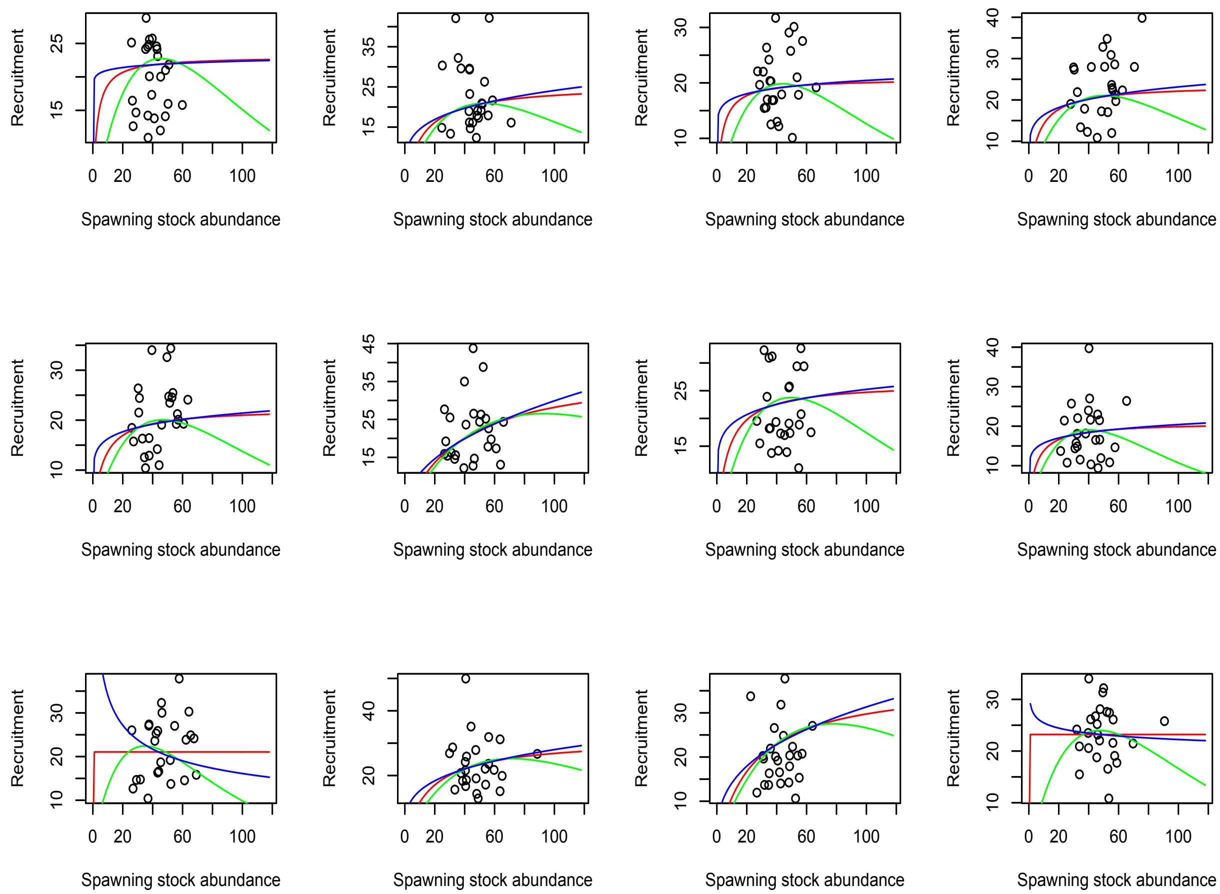
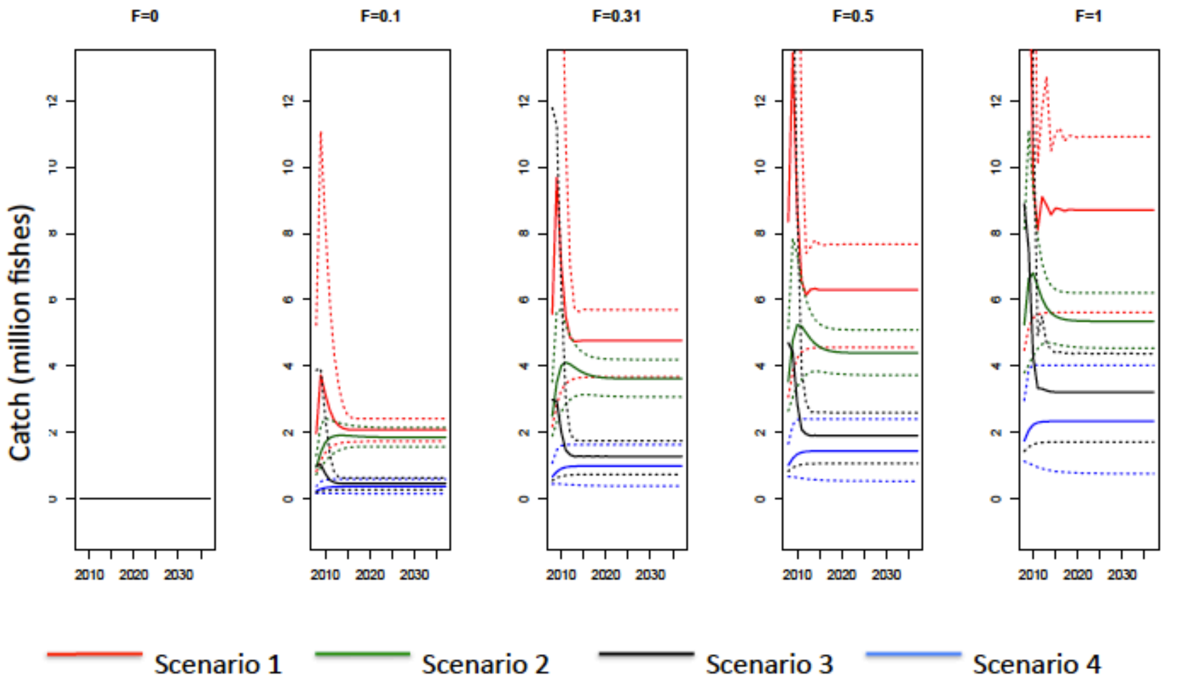


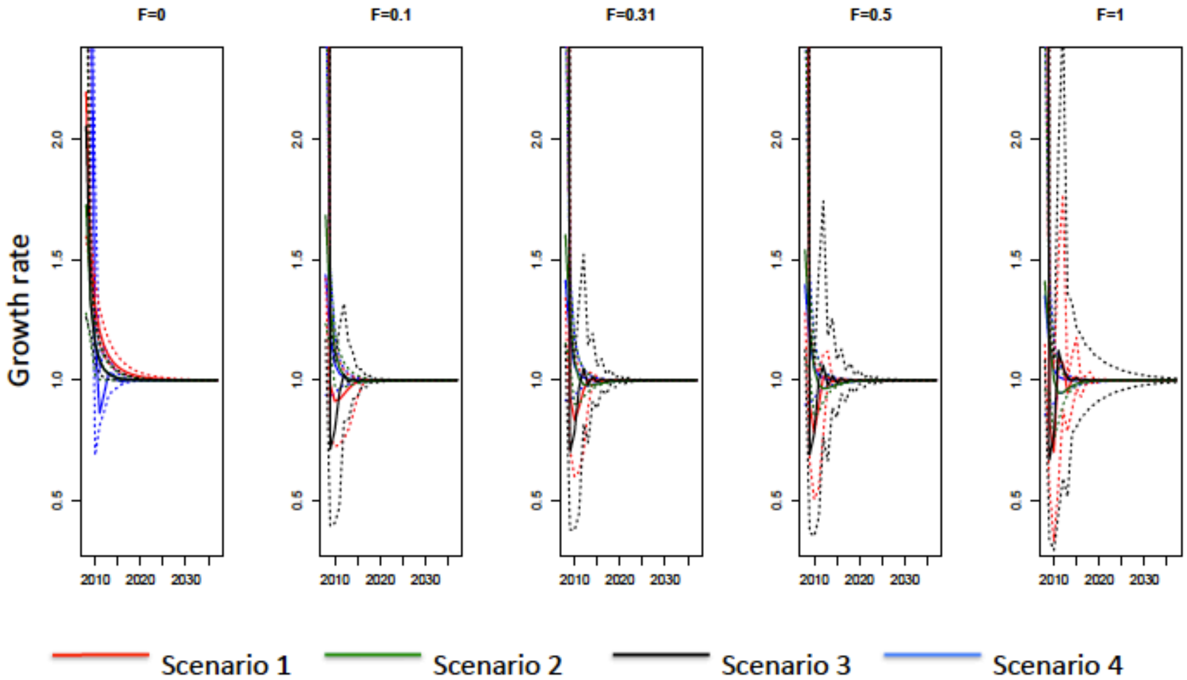
Figure 4.2. Plots of relationship between spawning stock and recruitment fitted by Beverton-Holt model, Ricker model, and Cushing model. Red lines represent Beverton-Holt model, green lines represent Ricker model, and blue lines represent Cushing model.

(a)



F=0
F=0.1
F=0.31
F=0.5
F=1
Catch (million fishes)
0
2
4
6
8
10
12
2010
2020
2030
Scenario 1
Scenario 2
Scenario 3
Scenario 4

(b)


F=0
F=0.1
F=0.31
F=0.5
F=1
Growth rate
0.5
1.0
1.5
2.0
2010
2020
2030
Scenario 1
Scenario 2
Scenario 3
Scenario 4

(c)

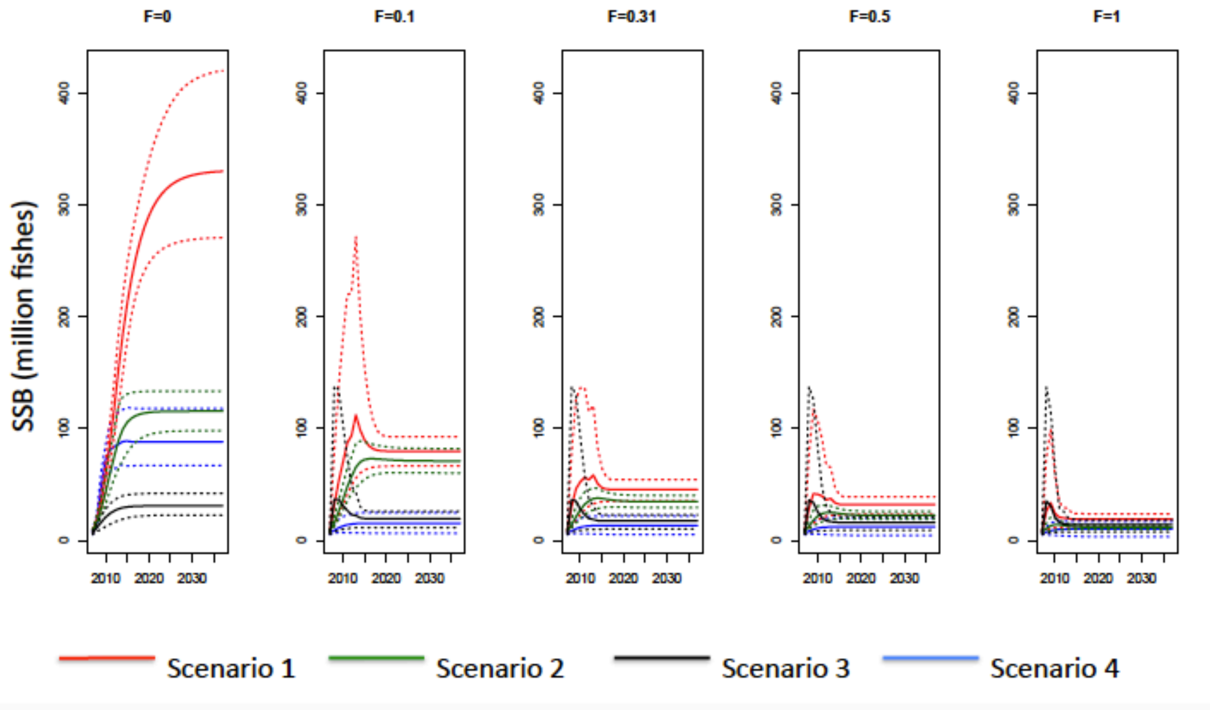


Figure 4.3. Changes of population growth rate, SSB, Total catch over time given 5 fishing mortality levels (0, 0.1, 0.31, 0.5 and 1) based on four scenarios in the population projection. (a) Total allowable catch (TAC); (b) Growth rate; (c) Spawning stock biomass.

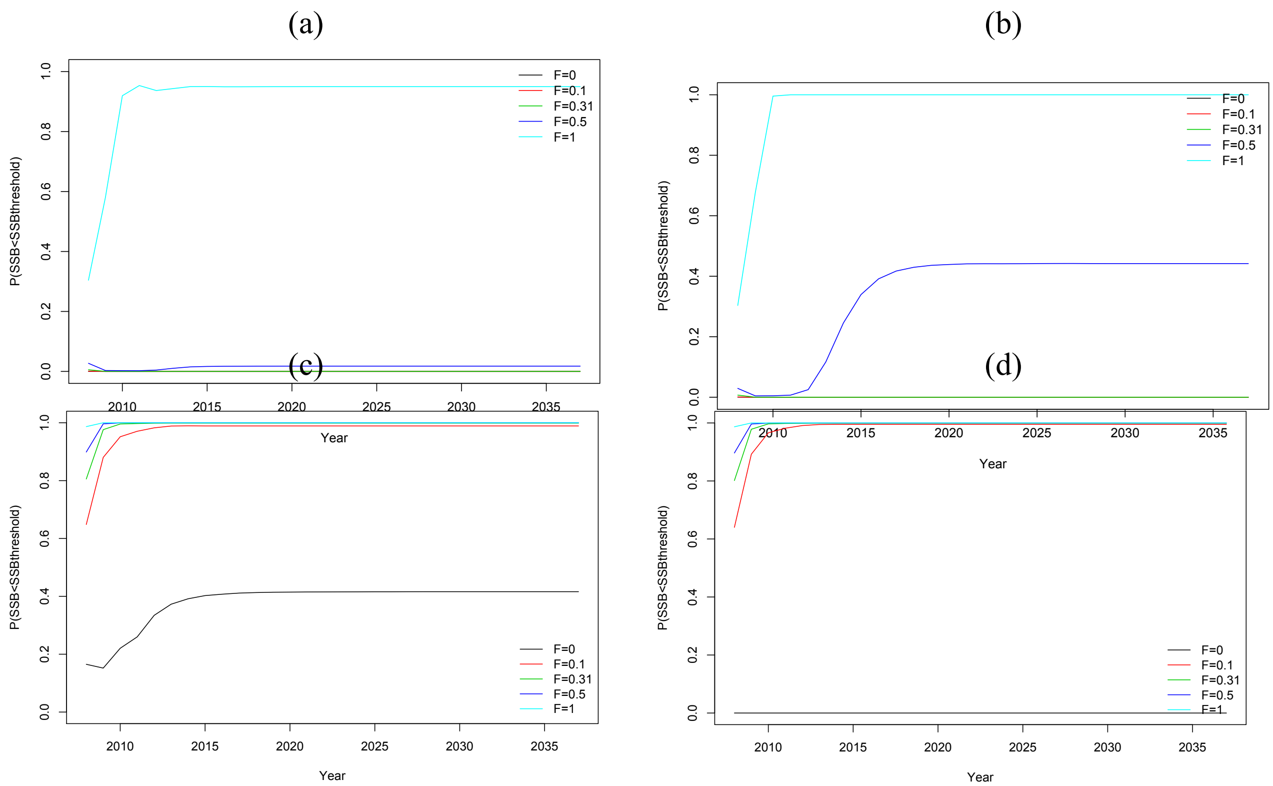


Figure 4.4. Risks of population being overfished based on different models. (a) Scenario 1: Stationary SCA with Beverton-Holt model; (b) Scenario 2: Stationary SCA with Ricker model; (c) Scenario 3: Non-stationary SCA with Beverton-Holt model; (d) Scenario 4: Non-stationary SCA with Ricker model.

Chapter 5

Summary

In this study, I evaluated the performance of spatial, non-spatial, and nonlinear models in analyzing Atlantic Weakfish distribution and explored the influence of environmental factors on Atlantic Weakfish distribution. I also explored variation in the spatial and temporal abundance of Weakfish using standardized catch rate and compared Weakfish abundance indices in inshore area and offshore area with specific focus on their differences in year trend. I also performed management strategies evaluation based on different statistical catch-at-age models and stock-recruitment models to evaluate different F-based management strategies.

Delta-GAM and Delta-SAR error model were selected to explore the spatial characteristics and nonlinearity in temporal and spatial distribution of Weakfish since they had smallest testing error and training error among the six candidate models. The result of model selection indicated that the Delta-GAM model managed to capture the nonlinear relationship between Weakfish and environmental factors; and Delta-SAR error model was able to capture the spatial autocorrelation in distribution of Weakfish.

Then the two models were further applied to other two fishery independent survey datasets. The distribution and standardized annual abundance index turned out to vary from year to year based on these models. The NMFS trawl, which focuses on deep-water area, showed slightly increasing trend in mid-2000s. The CHESMMAP, a survey in Chesapeake Bay, year trend was decreasing; while NEAMAP, a survey along coastal area of western Atlantic, shown slightly increasing trend by 2013. The differences among the Weakfish relative density to other environmental factors, such as water temperature, salinity and depth, were different in three surveys also. Our study based on the three surveys indicated that there is strong spatial heterogeneity in CPUE year trend even in well-designed surveys. Future stock assessment of Atlantic Weakfish should address the spatial heterogeneity of catch rate year trend.

In order to evaluate the current management strategies, five stock-recruitment models as well as two types of statistical catch-at-age model (stationary and nonstationary) were combined together to simulate data in the "future". The five stock-recruitment models were first compared, and two of them were selected into the simulation step. Five management measures were also considered. The results of the MSE indicate that the current F-based management strategy for Weakfish appears to meet the management sustainability goals when the actual resource dynamics are consistent with the current stock assessment with alternative stock-recruitment relationships. However the appropriateness of the biomass-based reference point used to evaluate probability of the population being lower than the reference point depends on the stock assessment models selected. The current biomass-based reference point tends to be high if the true population dynamics has nonstationary natural mortality.

This study helps improve our understanding of the Weakfish distribution, catch rate standardization and management of fisheries. The commonly used delta models of GLM and GAM were extended to spatial autoregressive models. The standardized catch rate showed different patterns of Weakfish trend. Future work may consider combining the nonlinearity and spatial autocorrelation in one model to conduct catch rate standardization. My risk assessment indicated that the lower fishing mortality could quickly increase population size and is more robust to the risk of overfishing and being overfished. In future studies, the economic income and human dimensions associated with harvesting should also be considered. In the evaluation of stock-recruitment models, the Ricker model and Beverton-Holt model were shown to be the best two models, consistent with the models that are now being used for stock assessment for Weakfish.

The MSE and risk assessment framework provides a useful approach for biologists and managers to explore population dynamics and assess a series of possible management strategies. This type of framework can also be applied to other fish species. Continued update of the population dynamics results with "new" data available through a Bayesian approach can improve the risk assessment by better evaluating the recommended restoration strategies.