Influence of the Estimator Selection in Scalloped Hammerhead Shark Stock Assessment

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Abstract

In natural sciences, frequentist paradigm has led statistical practice; however, Bayesian approach has been gaining strength in the last decades. Our study assessed the scalloped hammerhead shark population on the western North Atlantic Ocean using Bayesian methods. This approach allowed incorporate diverse types of errors in the surplus production model and compare the influences of different statistical estimators on the values of the key parameters (*r*, growth rate; *K* carrying capacity; depletion, F_{MSY} , fishing levels that would sustain maximum yield; and N_{MSY}, abundance at maximum sustainable yield). Furthermore, we considered multi-levelpriors due to the variety of results on the population growth rate of this species. Our research showed that estimator selection influences the results of the surplus production model and therefore, the value of the target management points. Based on key parameter estimates with uncertainty and Deviance Information Criterion, we suggest that state-space Bayesian models be used for assessing scalloped hammerhead shark or other fish stocks with poor data available. This study found the population was overfished and suffering overfishing. Therefore, based on our research and that there was very low evidence of recovery according with the last data available, we suggest prohibition of fishing for this species because: (1) it is highly depleted (14% of its initial population), (2) the fishery status is very unstable over time, (3) it has a low reproductive rate contributing to a higher risk of overexploitation, and (4) the easiness of misidentification among different hammerhead sharks (smooth, great, scalloped and cryptic species).

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List of Abbreviations Used

ACLs – Annual Catch Limits

AMs – Accountability measures

BRDs – by-catch reduction devices

CITES – Convention on the International Trade in Endangered Species

DIC – Deviance Information Criterion

DPS – Distinct Population Segment

EEZ – Exclusive Economic Zone

ESA – U.S. Endangered Species Act (ESA)

FAO – Food and Agriculture Organization of the United Nations

FL – Fork Length

FMP – Fishery Management Plan

F_{MSY} – Fishing mortality at Maximum Sustainable Yield

HMS – Highly Migratory Species

IUCN – World Conservation Union's International Union for the Conservation of Nature

LCS – Large Coastal Sharks

LRCI – Likelihood Ratio Confidence Interval

MLE – Maximum Likelihood Estimate

MSY – Maximum Sustainable Yield

MCMN – Markov chain Monte Carlo

NMFS – National Marine Fisheries Service

N – Abundance in Numbers

N_{MSY} – Abundance at Maximum Sustainable Yield

NOAA – National Oceanic and Atmospheric Administration

PS – Pelagic Shark

SCS – Small Coastal Sharks

SEDAR – Southeast Data Assessment and Review

TL – Total Length

Chapter 1 – Introduction

Many shark populations in all areas have significantly declined in the last few decades (Myers et al. 2007). Reasons are believed to be the slow intrinsic rates of increases of the sharks and overexploitation from the directed-shark fishery and by-catch (Kotas *et al*. 2011). Studies to help understand the fishery status and the influence of the fisheries on the shark populations are critically needed for managing these shark populations. This study focused on the scalloped hammerhead shark *Sphyrna lewini* (Griffith and Smith, 1834), a species globally exploited and classified as "Endangered" by the Union for Conservation of Nature (IUCN, 2013).

Past reports on scalloped hammerhead sharks in the western North Atlantic Ocean have concluded that the population has decreased; however, different researchers have provided diverse results on the degree of the decline (Baum et al. 2003; Burgess et al. 2005;Baum et al. 2005, Myers et al. 2007; Hayes et al. 2009). In this study, logistic surplus production models with different consideration of errors and estimators were compared to determine which one should be used. Past research (Punt 1992, Punt and Hilborn 1997; de Valpine and Hastings 2002; He 2010) has demonstrated that types of errors considered and estimator selection are important issues to assess the fishery, because these factors influence the stock assessment results. We applied three types of estimators (frequentist, likelihood, and Bayesian) and took two kinds of errors into account (measurement error and process-measurement error) to check the influences of these errors and statistical approaches on the key parameter estimations of the scalloped hammerhead shark population(r, K, depletion, F_{MSY} and N_{MSY}). The influence of statistical estimator on parameters estimates would be diagnosed so that recommendations on estimators to assess the scalloped hammerhead shark stock could be made.

Sharks Overfishing

Exploitation is the greatest threat to survival of the majority of marine species (McCleanachan *et al.* 2011). According to the IUCN red list (2013), of the 1,045 chondrichthyan species assessed globally (sharks, rays, and chimaeras), 2 % are Critically Endangered, 6% are Endangered, 11% are Vulnerable, 13% are Near Threatened, 23% are Least Concern, and 47% are Data Deficient (Camhi et al.2009; Figure 1.1). The decline of large predatory sharks in many parts of the world's oceans is a reality. Shark populations are mainly declining due to overfishing, followed distantly by habitat destruction and pollution *(*Ferreti et al. 2010; Figure 1.2). Overfishing is the depletion of a fish stock due to an excess of fishing. Overfishing has led to the existence of a high number of threatened species globally, such as *Sphyrna lewini* listed as globally Endangered (EN) by the IUCN. Fishing-induced mortality of sharks comes from directed targeting of sharks by fisheries, from by-catch (indirect catch of non-targeted fish), and through finning (kind of fishing which only uses shark fin and discards the rest of the fish) (Dulvy and Forrest, 2010). By-catch in other fisheries such as, purse seine fisheries, pelagic longline tuna, and swordfish fisheries is the main mortality cause for the scalloped hammerhead shark, above targeted fishing *(*Ferreti et al.2010; Figure 1.2).

In the 1930s, industrial shark fisheries were developed due mainly to the demand for vitamin A. Shark liver contains rich natural oil with high values of vitamin A, and it was the principal source of this vitamin during the Second World War. Although most of these fisheries disappeared by the 1950s, when the shark decline started and synthetic vitamin A was created and commercialized, another directed shark fishery developed in the 1980s in response to a growing demand for shark fins (Walker 1998). Although Asian countries have been trading with shark fins for ages, it has been in the last few decades when they have reach high prices in their markets (Ferreti et al. 2010). In many parts of Asia, shark fins are considered a valuable aphrodisiac, resulting in one of the most expensive fishery products in the world (Walker 1998). Furthermore, shark teeth and vertebrae are used in jewelry, shark liver oil (squalene) is used for medical purposes such as vaccines and sunscreens, shark cartilage is used in alternative medicine, and shark skin is used to make leather products such as wallets and shoes (Shark Angels 2011). However, few fisheries use all parts of the animals; most use only one part of the animal and waste the rest contributing to an excessive decline of the stocks (Walker 1998).

The directed-shark fisheries and the high shark by-catch in other fisheries, combined with the sharks' late age of maturity and slow growth and low fecundity rates, have caused the populations of many shark species to decline rapidly around the world. The low population resilience of sharks due to their life history strategies is cause to support lower levels of fishing before they become depleted (Musick *et al.* 2000). For the case of *Sphyrna lewini*, it has been proved that the population was much more abundant in the last thousands of years, and that it is experiencing a bottleneck for unknown causes (Nance et al. 2011). To avoid depletion before it is too late, by-catch could be reduced using by-catch reduction devices (BRDs), such as escape panels and grids, and shark repellent-technologies, such as magnets or chemical repellents (Brewer et al.1998). Furthermore, if the translation of threatened status to legal protection would be more efficient, some populations could recover in a shorter time. Nowadays, the Convention on the International Trade in Endangered Species (CITES 2008) is not satisfactory in listing sharks and rays; only one, the vulnerable white shark (*Carcharodon carcharias*), is listed on CITES Appendix II (McCleanachan et al. 2011). There are some national plans of action for sharks implemented by the Food and Agriculture Organization of the United Nations (FAO), but these are voluntary and have only been completed by a small number of countries (Techera and Klein 2011).

Besides all these control measurements that could implement, there is a need to better understand the dynamics of shark populations so that effective conservation strategies can be applied to avoid overfishing. Population dynamics models have a big range of uncertainty that also can contribute to the overfishing of the stocks. The choice of model can profoundly affect the final results of the assessment (Braccini et al. 2011; Simpfendorfer et al. 2011). This study examined estimator selection procedures in the case of the scalloped hammerhead shark to ensure that assumptions made in the model are valid and most appropriate estimator(s) is selected. We selected estimator/model based on the model selection criteria such as DIC values (Deviance Information Criterion) and whether or not the confidence or credible intervals are reasonable represented in the results.

Scalloped Hammerhead Shark Biology

Sphyrna lewini belongs to the family Sphyrnidae, which consists of all known hammerhead sharks (see taxonomic classification in Table 1). They are named by the characteristic shape of their heads, flattened and laterally extended, which resembles a hammer. *S.lewini* is characterized by a central indentation on the anterior margin of the head, along with two more indentations on each side of the central one. These indentations give them the common name of scalloped hammerhead shark. Their body is fusiform and their coloration varies from grey to grayish brow, bronze or olive on top on the body. The underside is pale yellow or white with dusky or black pectoral fin tips (Bester 2011, Miller et al. 2013).

Sphyrna lewini lives near the coast and adjacent pelagic waters in temperate and tropical seas (Compagno, 1984). This species is globally distributed (Figure 1.3), highly mobile and partially migratory, occurring as solitary individuals, pairs or in school (Maguire et al. 2006, Miller et al. 2013). Scalloped hammerhead sharks live in diverse habitats, since shallow bays and estuaries, to continental shelves and adjacent waters. The schooling behavior of adults is more common offshore over seamounts and near islands (Compagno 1984, Hearn et al.2010, Bessudo et al. 2011) while neonates and juveniles inhabit nearshore nursery areas (Duncan and Holland 2006, Miller 2013). They are considered opportunistic predators due to the variety of their diet: teleosts, cephalopods, crustaceans, and rays (Compagno 1984, Miller at al. 2013). Scalloped hammerheads are found from the surface to depths of up to 980m (Jorgensen et al. 2009). This wide distribution makes them accessible to be caught during different commercial fishing activities such as trawling, longlining and gillnetting in addition to artisanal fishing (Hazin et al. 2000).

Despite common worldwide occurrence of this shark species, little is known of the life history of scalloped hammerheads and what is known is often contradictory (e.g., Branstetter 1987; Piercy et al. 2007; Table 1.2). Females are sexually mature at larger sizes than males. Females matures around 200-250 cm (Total Length, TL) and males around 128-200 cm; however, reports differ on when they reach sexual maturity (Table 1.3). Branstetter (1987) showed that males are sexually mature at 1.8 m and females at 2.5 m. However, he recognizes there is a lack of data on females, because catches are dominated by males in the majority of studies (Hazin et al. 2001), and assumes that it is because females are associated more with deep oceanic waters than shelf waters. Klimley (1981) corroborated this hypothesis. He found that offshore aggregations of *S.lewini* are dominated by females in the Gulf of California because they move-off-shore at smaller sizes than males, where they feed on more pelagic prey. Later, Piercy et al. (2007) re-examined age and growth of scalloped hammerhead populations (using 309 samples), and he asserted that Branstetter used a low sample size, 25 individuals. Therefore Branstetter's results may not be credible. Piercy et al. results also showed that parameters and growth rates differed between males and females. Females had a lower growth coefficient, and higher asymptotic size (233.1cm Fork Length) than males (214.8 cm FL).

Research suggests slower growth rates of scalloped hammerheads in the Atlantic Ocean than in the Pacific Ocean (Piercy et al. 2007). In the southern Brazilian coast, Kotas and others (2011), found that both sexes have a similar low growth coefficient but they observed that females reached larger sizes than males at the same age (males 266 cm, females 300cm; Table 1.2). Although there are diverse results about length and age at maturity of scalloped hammerhead shark, we can summarize that total length at maturity varies by sex and the age of maturity varies by regions. However, the difference in growth could be due to interpretation of vertebrae band formation used for aging rather than geographic differences. Pacific studies assume band formation is biannual whereas Atlantic studies assume an annual formation (Table 1.3). Vertebrae for age determination are collected in sharks to calculate the number of the opaque bands (summer growth, calcified) and the translucent bands (winter growth, hyalines). On one hand, Chen et al. (1990) and Tolentino and Mendoza (2001) believed there are two growth bands per year. On the other hand, Piercy et al. (2007) suggested that one growth-band deposition occurs annually, at least in juvenile scalloped hammerheads (Table 1.3). Validation of band formation is still needed in adults. Piercy et al. (2007) found that the oldest aged shark was 30.5 years for both sexes; however, according to Kotas et al. (2011), *S.lewini* from the southern Brazilian coast grows slower and is longer lived than in the other regions. Their longevity estimate for males and females was 55 years (Table 1.3). Although more investigations are needed, it seems likely that *Sphyrna lewini* has annual band formation as other Chondrichtyan (Campana et al. 2002; Okamura and Semba 2009).

Scalloped hammerhead sharks have internal fertilization and viviparity, with a gestation period over 8-12 months. Birth occurs predominantly in October and November and neonates range from 37 to 57 cm (Table 1.2). The litter size is from 10 to 40 pups (Branstetter, 1987; Liu and Chen, 1999). *Sphryna lewini* produces large litters of relatively small pups due probably to heavy predation on the young (by subadult and adult males of this species and by other common coastal sharks; Clarke, 1971). According to Dulvy and Forrest (2010), juvenile survival is one the main determinants of the resilience of shark population to fishing. Therefore, the population may be dependent on the production of large cohorts to sustain the adult population. However, such effects can be reduced in scalloped hammerhead sharks because they employ a nursery ground for their young (Gruber et al. 2001; Heupel and Simpfendorfer 2002). There is a high risk of overexploitation because their schooling behavior allows fishers to capture them in great number. Therefore, scalloped hammerhead sharks, like other elasmobranches, may require conservative management strategies because they tend to be very susceptible to overexploitation (Musick, 2000).

Distribution Area and Subpopulations

The phylogenetic origin of *S. lewini* is the Indo-Pacific ocean and, possibly, also the West Pacific ocean, with subsequent dispersal into the Atlantic and into the Central and Eastern Pacific (Figure 1.3). Males disperse across open oceans and they are responsible for gene flows among global populations of scalloped hammerheads (Daly-Engel et al. 2012). Scalloped hammerhead shark is a highly migratory species (HMS); however, sexual segregation occurs as in other elasmobranch species (Klimley 1987). Females move around the coastline, across continue nursery habitat, but rarely across open oceans as males. However, females disperse earlier than males.

Five subpopulations of scalloped hammerhead sharks are recognized by the IUCN: the Eastern Central and Southeast Pacific (Endangered), the Eastern Central Atlantic (Vulnerable), the Northwest and Western Central Atlantic (Endangered), the Southwest Atlantic (Vulnerable), and the Western Indian Ocean (Endangered). In the Western Atlantic, the species lives from New Jersey to Uruguay, including the Gulf of Mexico and the Caribbean. The Northwest and West Central Atlantic population ranges from New Jersey to the Caribbean. It is not separated by a physical barrier from other populations in the Atlantic Ocean, but it is distinct physiologically. Chapman et al. (2009) showed genetic distinctions between the Northwest Atlantic, Caribbean Sea and Southwest Atlantic as well as from the Eastern Central Atlantic, Indian Ocean, and Pacific populations.

The last status review of the scalloped hammerhead shark by National Marine Fisheries Service (NMFS; Miller et al. 2013), identified six Distinct Population Segments (DPSs), one population more in the Pacific Ocean than with the IUCN criteria(Table 1.6). The NMFS National Oceanic and Atmospheric Administration (NOAA) sets the following DPSs based on genetic variation, behavioral and physical factors, and differences in international regulatory mechanisms:a Northwest Atlantic and Gulf of Mexico DPS, Central and Southwest Atlantic DPS, Eastern Atlantic DPS, Indo-West Pacific DPS, Central Pacific DPS, and Eastern Pacific DPS of scalloped hammerhead shark. They only found a high risk of extinction in the Eastern Atlantic DPS and the Eastern Pacific DPS (Endangered; Table 1.6) and listed as threatened, the

Central & SW Atlantic and Indo-West Pacific DPSs. Two DPSs did not warrant listing, the NW Atlantic & GOM DPS and the Central Pacific DPS (Miller et al. 2013).

Furthermore, there was found a cryptic species, identical to *S.lewini*, that lives from South Carolina to Brazil and it can only be differentiated with genetic analysis (Pinhal et al. 2012). Catches of this cryptic species may have been included in the scalloped hammerhead catch data and therefore, overestimating the population (Miller et al. 2013).

Scalloped Hammerhead Shark Management and Research

Sharks have been heavily harvested in the Gulf of Mexico and northwest Atlantic Ocean since the 1980s (NMFS 2003). In 1989, the National Marine Fisheries Service (NMFS) began managing sharks within the U.S. Exclusive Economic Zone (EEZ = 200 miles from the coast). The most frequently caught sharks were grouped into three categories, Large Coastal (LC), Small Coastal (SC), and Pelagic (PS), because catch data for single species and life history information were limited (Piercy et al. 2007). The Large Coastal Shark (LCS) category is formed by 11 species and the three hammerhead sharks (*Sphyrna* spp.) are currently managed as part of this complex in the United States (Table 1.4):

- smooth hammerhead shark (*Sphyrna zygaena*) (Vulnerable, 2005),
- scalloped hammerhead shark (*Sphyrna lewini*) (Endangered, 2007),
- great hammerhead shark (*Sphyrna mokarran*) (Endangered, 2007).

Recent stock assessments of the LCS complex indicate that its status has improved since 1998, but that it is likely to be overfished ($N_{current}/N_{msy} < 1$) and overfishing is still occurring ($F_{current}/F_{msy} > 1$) (Cortés et al. 2002). The first LCS assessment was completed in 1992 and resulted in the first shark Fisheries Management Plan (FMP) in 1993. It established recreational catch limits and commercial quotas by group (Table 1.4). The 1996 LCS assessment concluded that the population was overfished and experiencing overfishing. In 1998, sandbar sharks and (*Carcharhinus plumbeus*), and blacktip sharks (*C. limbatus*) were assessed by themselves, and like as the LCS complex, they were overfished. In 2002, the complex was still overfished and experiencing overfishing; however, the blacktip shark stock was healthy and sandbar shark stock was near the threshold to be healthy (Cortés et al. 2002). The last assessment was conducted by SEDAR in 2006. “Southeast Data, Assessment, and Review (SEDAR) is a cooperative Fishery Management Council process initiated in 2002 to improve the quality and reliability of fishery stock assessments in the South Atlantic, Gulf of Mexico, and US Caribbean (NMFS 2011a)”. SEDAR estimated that the LCS complex and the blacktip shark stock were not overfished nor experiencing overfishing, although the sandbar shark fishery was overfished and overfishing was still occurring (NMFS 2006).

These assessments evaluated the LCS as a complex (except for blacktip and sandbar species); however, species-specific stock assessments are essential to really know the status of each species in the complex. The decline of the three species of hammerhead shark has been documented in the U.S waters since the 1980s (Hayes 2008). The present study focuses on the scalloped hammerhead shark because the species is relatively more abundant than the other 2 species, and there are more surveys available. Hayes (2008) carried out the first species-specific stock assessments of *Sphyrna lewini* using all the data available. We compared his results (using frequentist methods) with our estimates of the key parameters using other statistical estimators (likelihood and Bayesian) to know their influence on the final results.

The past research studies on the status of scalloped hammerhead shark population have obtained variable results:

- Baum et al. (2003), showed an 89% decline of the population.
- Myers et al. (2007), showed a 98% decline of the population.
- Hayes et al. (2009), showed an 83% decline of the population.

Findings of Baum et al. and Myers et al. are likely not accurate because each study used only a single relative abundance index: the pelagic logline logbook data set and the North Carolina bottom longline survey, respectively (Burgess et al. 2005, Baum et al. 2005). Furthermore, only the frequentist estimator (considering only measurement error) was used in these studies and uncertainty of these estimates were not all presented. Hayes et al. (2009) used all the data available and took into account observation error; however, they also only used the frequentist estimator. Jiao et al. (2009b, 2011) assessed the hammerhead shark complex using the Bayesian analysis and considering both process error and measurement error in their model, but they did not assess the scalloped hammerhead shark by itself. Therefore, this study assessed the scalloped hammerhead shark population by itself using different estimators, including Bayesian approach. This approach allowed the comparison of the key parameters estimates from different statistical paradigms (frequentist, likelihood and Bayesian) and from different kind of errors (measurement vs. measurement-process error).

In April of 2011, the NMFS reported that the scalloped hammerhead shark was still overfished and experiencing overfishing based on the results of Hayes et al. (2009). Therefore, NMFS must take action to end or prevent overfishing in the fishery and to implement a rebuilding plan within two years of making this determination. Furthermore, this plan has to establish a mechanism for specifying and actually specify Annual Catch Limits (ACLs) and Accountability Measures (AMs) to prevent overfishing (NMFS 2011b).

Currently, the scalloped hammerhead sharks are not listed in the U.S. Endangered Species Act (ESA). However, due to the unhealthy situation of the different stocks recognized by NMFS, in August of 2011, two associations carried out the petition to list the scalloped hammerhead shark under the ESA either worldwide or as one or more distinct population segments (DPS; WildEarth Guardians and Friends of Animals 2011). This petition was submitted to the U.S. Secretary of Commerce, acting through the National Oceanic and Atmospheric Administration (NOAA) and the National Marine Fisheries Services (NMFS). A species must satisfy at least one of five listing criteria (1.Destruction or modification of habitat; 2.Overutilization for commercial, recreational, scientific, or educational purposes; 3.Disease or predation; 4. Inadequacy of existing regulatory mechanisms; or 5. Other natural or human factors) in order to qualify for listing as a "threatened" or "endangered" species under the ESA. The scalloped hammerheads or any of the DPS's of the species, may qualify as "threatened" or "endangered" due to overutilization for commercial and recreational purposes, the inadequacy of existing regulatory mechanisms, and other factors, including low reproductive rates causing higher risk of overutilization. After reviewing the information contained in the petition, NMFS concluded the petition presents substantial scientific information indicating the petitioned action of listing the scalloped hammerhead shark as threatened or endangered may be warranted. Therefore, in accordance with the ESA and NMFS implementing regulation, they have conducted a status review report (Miller et al. 2013). This report has two parts: the "Status Review" of the species with the best available information, and the "Assessment of Extinction Risk" for the species. The report identified six DPSs of the scalloped hammerhead shark (table

1.6) and concluded that: “ the Central Pacific DPS was at a very low risk of extinction now and in the foreseeable future, the Northwest Atlantic & Gulf of Mexico DPS was at a low risk of extinction now and in the foreseeable future, the Central & Southwest Atlantic DPS and the Indo-West Pacific DPS were at a moderate risk of extinction now and in the foreseeable future, whereas the Eastern Atlantic DPS and Eastern Pacific DPS were at a high risk of extinction now and in the foreseeable future (Miller et al. 2013)”. Therefore, the scalloped hammerhead shark population of interest here is not going to be listed in the U.S. Endangered Species Act in the near future, but they found that the main threat to this population was the high at-vessel fishing mortality, with overutilization by both commercial and recreational fisheries.

Types of Estimator

A good knowledge of the population dynamics is needed to manage a fish stock with reasonable quality; thus, mathematical models are used to describe the dynamics of the population of interest. However, these models often have assumptions in order to simplify the dynamics of the fish population or restricted by information available. New approaches and tools are needed to interpret uncertainties within the assessment models and to improve the quality of the fish stock assessment. Fisheries management has to take into account all types of uncertainties to determine the status of a fish stock and the exploitation rate reasonably. Uncertainty is usually categorized in four types: measurement errors, process errors, model errors and operating errors. Measurement error from inexact measurement, process error from the natural variability in the processes being modeled, model errors from the ignorance to describe the complex dynamics, and operating error from differences between the observed and effective fishing efforts, for example, the inability to control the fishery as we planned, such as landing above quota when quota is used in the control rule (Chen and Paloheimo, 1998). Thus, to estimate the parameters of the populations, the types of errors and a method of estimation have to be assumed to develop an objective function that will be optimized (Quinn and Deriso, 1999).

The method of estimation is a very important issue because it can change the results drastically when the model is fitted to the observed data (Punt 1992, Punt and Hilborn 1997; de Valpine and Hastings 2002; He 2010). Three kinds of estimators, based on their statistical paradigms, were used in this study: frequentist, likelihood, and Bayesian. Frequentist approach refers to the classical paradigm, standard methods such us hypothesis testing, estimation, and confidence intervals. Likelihood approach has features of the other two paradigms. It represents a missing concept in the classical approach. Likelihood ratio [$L(data|\theta_{MLE}) / L(data|\theta_0)$] gives us the opportunity to say how much a parameter estimate is supported by the data relative to the maximum likelihood estimate (MLE; Royall 1997, Jiao et al. 2009a). Lately, Bayesian methods are based on the likelihood approach, but it allows us to include within the model existing knowledge about the uncertainty in estimates of previous parameters.

Bayesian statistics uses algorithms such as Markov chain Monte Carlo (MCMC) to solve for the posteriors of the parameters (Punt and Hilborn 1997; Jiao et al. 2009b). Posterior is called to the posterior distribution of the key parameter, which results from the likelihood function times the prior distribution of the parameter (Bayes law [$p(\theta|data) \propto L(data|\theta)p(\theta)$]). Prior (prior distribution) summarized all the available knowledge about the parameter, except the data used to calculate the likelihood function (Punt and Hilborn 1997) .One of the advantages of Bayesian analysis is that it provides an estimation of parameter distribution, not just a single parameter value. During the last couple of decades, the uses of Bayesian techniques have quickly increased in the field of ecology due to the increases in computing power (Hobbs and Hilborn, 2006). Bayesian hierarchical analysis has been used to model data that are hierarchically structured, but is also used when multi-level priors are needed such as in this case. A simple Bayesian analysis uses a prior probability and the likelihood to compute the posterior probability. However, in Bayesian hierarchical analysis, this prior probability depends on other parameters. Therefore, this prior probability is replaced by likelihood and the prior probability on the new introduced parameter or parameters. These kinds of priors are called multi-level priors, which have been proven to be more robust than single-level priors (Andrews et al. 1993; Roberts and Rosenthal 2001; Clark 2003). In the case of the scalloped hammerhead shark, multiple studies have derived different results on population growth rate, which encouraged us to consider multi-level priors (Jiao et al. 2009b).

The type of error to be considered is another source of uncertainty. When only the measurement error is considered, the estimator is called measurement error estimator; when both measurement and process errors are considered, the corresponding estimator is called a process-measurement error estimator. The surplus production model is often called state-space surplus production model when both process and measurement errors are considered. In the state-space time series models, such as those used in the population dynamics of shark species, measurement error is usually considered but not for the process error in many cases (Hayes et al. 2009; NMFS, 2006). However, results of parameter estimation in past studies found that if process error is considered in a state-space time series model, it may dramatically change the results (de Valpine and Hastings 2002; Polacheck et al. 1993; He 2010). Wade (1999) used different estimators using different statistical paradigms and found that point estimates from each method were similar, but credible or confidence intervals varied considerably. Based on the fact that the most current stock assessments of scalloped hammerhead sharks were using frequentist estimator and only take into account the observation error (Baum et al. 2003; Myers et al. 2007; Hayes et al. 2009), a comprehensive study was needed to determine how the statistical estimator influences the value of the key parameters estimated (*r*, *K*, Depletion, F_{MSY} and N_{MSY}).

The goals of this study were to evaluate the utility of different estimators (frequentist, likelihood and Bayesian) when limited data are available (as *Sphyrna lewini* case) and to determine the degree of the influence on the scalloped hammerhead shark stock assessment when different types of errors are used. More specifically, we would:

(1) Compare the influence of the statistical estimators (frequentist, likelihood, and Bayesian) on key parameters such as such as *r*, *K*, initial depletion, and fishery/population status, when only measurement error is considered.

(2) Compare the influence of error (measurement error and process-measurement error considered) consideration on key parameters such as such as *r*, *K*, initial depletion, and fishery/population status, using Bayesian and Bayesian hierarchical estimators.

References

Adams, D.H. and R. Paperno. 2007. Preliminary assessment of a nearshore nursery ground for the scalloped hammerhead off the Atlantic Coast of Florida. American Fishery Society Symposium 50: 165-174.

Andrews, R. W., J. O. Berger, and M. H. Smith. 1993. Bayesian estimation of manufacturing effects in a fuel economy model. Journal of Applied Econometrics, Supplement: Special Issue on Econometric Inference Using Simulation Techniques 8: 5–18.

Bass, A. J., J. D. D'Aubrey, and N. Kistnasamy. 1975. Sharks of the east coast of southern Africa. 111. The families Carcharhinidae (excluding *Mustelus* and *Carcharhinus)* and Sphyrnidae. South African Association for Marine Biological Research. Oceanographic Research Institute Investigational Report 38: 100 pp.

Baum, J. K., D. G. Kehler, and R. A. Myers. 2005. Robust estimates of decline for pelagic shark populations in the northwest Atlantic and Gulf of Mexico. Science 299, 389-392.

Baum, J. K., R. A. Myers, D. G. Kehler, B. Worm, and S. J. Harley. 2003. Collapse and conservation of shark populations in the northwest Atlantic. Science 299, 389-392.

Bejarano-Álvarez, M., F. Galván-Magaña, and R. I. Ochoa-Báez. 2011. Reproductive biology of the scalloped hammerhead shark *Sphyrna lewini* (Chondrichthyes: Sphyrnidae) off south-west Mexico. Aqua 17: 11–22.

Bessudo, S., G. A. Soler, A. P. Klimley, J. T. Ketchum, A. Hearn, and R. Arauz. 2011. Residency of the scalloped hammerhead shark (*Sphyrna lewini*) at Malpelo Island and evidence of migration to other islands in the Eastern Tropical Pacific. Environmental Biology of Fishes 91: 165–176.

Bester, C. 2011. Species Profile: Scalloped Hammerhead. Florida Museum of Natural History. Accessed July 5, 2013. http://www.flmnh.ufl.edu/fish/Gallery/Descript/Schammer/ScallopedHammerhead.html

Braccini, J. M., M. P. Etienne, and S. J. D. Martell. 2011. Subjective judgement in data subsetting: implications for CPUE standardisation and stock assessment of non-target chondrichthyans. Marine and Freshwater Research 62, 734–743.

Branstetter, S. 1987. Age, growth, and reproductive biology of the silky shark, (*Carcharhinus falciformis*) and the scalloped hammerhead, (*Sphyrna lewini*), from the northwestern Gulf of Mexico. Environmental Biology of Fishes 19(3):161-173.

Brewer, D., N. Rawlinson, S. Eayrs, and C. Burridge . 1998. An assessment of by-catch reduction devices in a tropical Australian prawn trawl fishery. Fisheries Research 36: 195–215.

Burgess, G. H., L. R. Beerkircher, G. M. Cailliet, J. K. Carlson, E. Cortés, K. J. Goldman, R. D. Grubbs, J. A. Musick, M. K. Musyl, and C. A. Simpfendorfer. 2005. Is the collapse of shark populations in the northwest Atlantic Ocean and Gulf of Mexico real? Fisheries 30:19-26.

Buencuerpo, V., S. Rios, and J. Morón. 1998. Pelagic sharks associated with the swordfish, *Xiphias gladius*, fishery in the eastern North Atlantic Ocean and the Strait of Gibraltar. Fishery Bulletin 96: 667-685.

Camhi, M. D, S. V. Valenti, S. V. Fordham, S. L. Fowler, and C. Gibson. 2009. The conservation status of pelagic sharks and rays: report of the IUCN shark specialist group pelagic shark red list workshop. IUCN Species Survival Commission Shark Specialist Group. Newbury, UK, 78 pp.

Capape, C., M. Diop, and M. N'Dao. 1998. Record of four pregnant females of the scalloped hammerhead, *Sphyrna lewini* (Sphyrnidae) in Senegalese waters. Cybium 22: 89–93.

Castro, J. I. 1993. The shark nursery of Bulls Bay, South Carolina, with a review of the shark nurseries of the southeastern coast of the United States. Environmental Biology of Fishes 38: 37-48.

Chapman, D. D., D. Pinhal, and M. S. Shivji. 2009. Tracking the fin trade: genetic stock identification in western Atlantic scalloped hammerhead sharks *Sphyrna lewini*. Endangered Species Research 9: 221-228.

Chen, C., T. Leu, and S. Joung. 1988. Notes on reproduction in the scalloped hammerhead, *Sphyrna lewini*, in northeastern Taiwan waters. Fishery Bulletin 86: 389-393.

Chen, C. T., T. C. Leu, S. J. Joung, and N. C. H. Lo. 1990. Age and growth of the scalloped hammerhead, *Sphyrna lewini*, in northeastern Taiwan waters. Pacific Science 44, 156–170.Chen, Y., and J. E. Paloheimo.1998. Can a more realistic model error structure improve the parameter estimation in modeling the dynamics of fish populations? Fisheries Research 38:9–17.

Clark, J. S. 2003. Uncertainty and variability in demography and population growth: a hierarchical approach. Ecology, 84: 1370–1381.

Clarke, T. A. 1971. The ecology of the scalloped hammerhead, *Sphyrna lewini*, in Hawaii. Pacific Science 25: 133-144.

Compagno, L. J. V. 1984. FAO species catalog. Vol 4. Sharks of the world. An annotated and illustrated catalog of shark species known to date. Part 2. Carcharhiniformes. FAO Fisheries Synopsis 125: 655 pp.

Cortés, E., L. Brooks, and G. Scott. 2002. Stock assessment of large coastal sharks in the U.S.Atlantic and Gulf of Mexico. Sustainable Fisheries Division Contribution SFD-02/03-177. NOAA, NMFS, Southeast Fisheries Science Center, Panama City, FL, 133 pp.

Dudley, S. and C. Simpfendorfer. 2006. Population status of 14 shark species caught in the protective gillnets off KwaZulu-Natal beaches, South Africa, 1978-2003. Marine and Freshwater Research 57: 225-240.

Dulvy, N. K. and R.E. Forrest. 2010. Life histories, population dynamics and extinction risks in chondrichthyans. In Sharks and Their Relatives, Vol. II. J. C. Carrier, Musick, J. A. , Heithaus M.R eds., pp: 639–679. Boca Raton, FL: CRC Press.

Duncan, K.M. and K.N. Holland. 2006. Habitat use, growth rates and dispersal patterns of juvenile scalloped hammerhead sharks *Sphyrna lewini* in a nursery habitat. Marine Ecology Progress Series 312: 211–221.

Ferreti, F., B. Worm, G.L. Britten, M.R. Heithaus, and H.K. Lotze. 2010. Patterns and ecosystem consequences of shark declines in the ocean. Ecology Letters, 13, 1055–1071.

Gruber, S.H., J. R. C. de Marignac, and J. M. Hoenig. 2001. Survival of juvenile lemon sharks at Bimini, Bahamas, estimated by mark-depletion experiments. Transactions of the American Fisheries Society 130:376–384.

Harry, A.V., W. G. Macbeth, A. N. Gutteridge. and C.A. Simpfendorfer. 2011. The life histories of endangered hammerhead sharks (Carcharhiniformes, Sphyrnidae) from the east coast of Australia. Journal of Fish Biology 78:2026-2051.

Hayes, C. 2008. Investigating single and multiple species fisheries management: stock status evaluation of hammerhead (*Sphyrna spp*.) sharks in the western North Atlantic and Gulf of Mexico. Master thesis, Virginia Polytechnic Institute and State University. 135 pp.

Hayes C., Y. Jiao, and E. Cortés. 2009. Stock assessment of scalloped hammerheads in the Western North Atlantic Ocean and Gulf of Mexico. North American Journal of Fisheries Management 29: 1406–1417.

Hazin, F., A. Fisher, and M. Broadhurst. 2003. Aspects of reproductive biology of the scalloped hammerhead shark *Sphyrna lewini*, off northeastern Brazil. Environmental Biology of Fishes 61:151–159.

He, Q. 2010. Investigating the performance of process-observation-error-estimator and robust estimators in surplus production model: a simulation study. Master's thesis,Virginia Polytechnic Institute and State University, Virginia.

Hearn, A., J. Ketchum, A. P. Klimley, E. Espinoza, and C. Peñaherrera. 2010. Hotspots within hotspots? Hammerhead shark movements around Wolf Island, Galapagos Marine Reserve. Marine Biology 157: 1899-1915.

Heupel, M. R., and C. A. Simpfendorfer. 2002. Estimation of mortality of juvenile blacktip sharks, *Carcharhinus limbatus*, within a nursery area using telemetry data. Canadian Journal Fisheries and Aquatic Science 59: 624–632.

Hobbs, N. T., and R. Hilborn. 2006. Alternatives to statistical hypothesis testing in ecology: a guide to self-teaching. Ecological Applications 16: 5–19.

IUCN 2013. IUCN Red List of Threatened Species. Available : www.iucnredlist.org. (September 2013).

Jiao, Y**.,** K. Reid, T. Nudds, and E. Smith. 2009a. Graphical evaluation of fishery status with a likelihood inference approach. North American Journal of Fisheries Management. 29:1106-1118.

Jiao, Y., C. Hayes, and E. Cortés. 2009b. Hierarchical Bayesian approach for population dynamics modelling of fish complexes without species-specific data. ICES Journal of Marine Science, 66: 367–377.

Jiao, Y., E.Cortés, K. Andrews, F. Guo. 2011. Poor-data and data-poor species stock assessment using a Bayesian hierarchical approach. Ecological Application 21: 2691–2708.

Jorgensen, S. J., A. P. Klimley, and A. F. Muhlia-Melo. 2009. Scalloped hammerhead shark, *Sphryna lewini*, utilizes deep-water, hypoxic zone in the Gulf of California Journal of Fish Biology 74: 1682-1687.

Klimley, A. P. 1981. Grouping behavior in the scalloped hammerhead. Oceanus 24: 65-71.

Klimley, A. P. 1987. The determinants of sexual segregation in the scalloped hammerhead shark, *Sphyrna lewini*. Environmental Biology of Fishes18: 27–40.

Kotas, J. E., V. Mastrochirico, and M. Petrere Jr. 2011. Age and growth of the Scalloped Hammerhead shark, *Sphyrna lewini* (Griffith and Smith, 1834), from the southern Brazilian coast. Brazilian Journal of Biology 71:3.

Lessa, R., R.C. Menni, and F. Lucena. 1998. Biological observations on *Sphyrna lewini* and *S. tudes* (Chondrichthyes, Sphyrnidae) from northern Brazil. Vie Milieu 48: 203–213.

Liu, K. M., and C. T Chen. 1999. Demographic analysis of the scalloped hammerhead, *Sphyrna lewini*, in the Northwestern Pacific. Fisheries Science 65: 218-223.

Maguire, J.J., M. P. Sissenwine, J. Csirke, R. J. R. Grainger, and S.M. Garcia. 2006. The state of world highly migratory, straddling and other high seas fisheries resources and associated species. FAO Fisheries Technical Paper. No. 495. FAO, Rome. 84p.

McCleanachan, L., A. B. Cooper, K. E. Carpenter, and N. K. Dulvy. 2011. Extinction risk and bottlenecks in the conservation of charismatic marine species. Conservation Letters 5:73-80.

Miller, M.H., J. Carlson, P. Cooper, D. Kobayashi, M. Nammack, and J. Wilson. 2013. Status review report: scalloped hammerhead shark (*Sphyrna lewini*). Report to National Marine Fisheries Service, Office of Protected Resources. March 2013.131 pp.

Musick, J. A., G. Burgess, G. Cailliet, M. Camhi, and S. Fordham. 2000. Management of sharks and their relatives (Elasmobranchii). Fisheries 25: 9–13.

Myers, R. A., J. K. Baum, T. D. Shepherd, S. P. Powers, and C. H. Peterson. 2007. Cascading effects of the loss of apex predatory sharks from a coastal ocean. Science 315: 1846-1850.

Nance, H. A., P. Klimley, F. Galván-Magaña, J. Martínez-Ortíz, and P. B. Marko. 2011. Demographic processes underlying subtle patterns of population structure in the scalloped hammerhead shark, *Sphyrna lewini*. PloS one 6(7),e21459.

NMFS (National Marine Fisheries Service). 2003. Final amendment 1 to the fishery management plan of the Atlantic tunas, swordfish and sharks. NOAA, Silver Springs, MD.

NMFS. 2006. SEDAR 11. Stock assessment report: large coastal shark complex, blacktip and sandbar shark. US Dept. Commerce, NOAA, NMFS, Highly Migratory Species, Silver Spring, MD, 387 pp.

NMFS. 2011a. SEDAR. Available : http://www.sefsc.noaa.gov/sedar/ (November 2011)

NMFS. 2011b. Endangered and threatened wildlife; 90-day finding on a petition to list the scalloped hammerhead shark as threatened or endangered under the Endangered Species Act. Federal register, USA. Available: http://www.federalregister.gov. (November 2011)

Noriega, R., J. M. Werry, W. Sumpton, D. Mayer, and S. Y. Lee. 2011. Trends in annual CPUE and evidence of sex and size segregation of *Sphyrna lewini*: Management implications in coastal waters of northeastern Australia. Fisheries Research, 110(3):472-477.

Okamura, H. and Y. Semba. 2009. A novel statistical method for validating the periodicity of vertebral growth band formation in elasmobranch fishes. Canadian Journal of Fisheries and Aquatic Sciences 66: 771-780.

Piercy, A. N., J. K. Carlson, J. A. Sulikowski, and G. H. Burgess. 2007. Age and growth of the scalloped hammerhead shark, *Sphyrna lewini*, in the northwest Atlantic Ocean and Gulf of Mexico. Marine and Freshwater Research 58: 34-40.

Polacheck, T., R. Hilborn, and A. E. Punt. 1993. Fitting surplus production models: comparing methods and measuring uncertainty. Canadian Journal of Fisheries and Aquatic Science 50: 2597-2607.

Punt, A. E. 1992. Management procedures for Cape hake and baleen whale resources. Benguela Ecology Programme Report 23, 689 pp.

Punt, A. E., and R. Hilborn. 1997. Fisheries stock assessment and decision analysis: the Bayesian approach. Review in Fish Biology and Fisheries.7: 35–63.

Quinn, R. J., and R. B. Deriso. 1999. Quantitative Fish Dynamics. Oxford University Press, New York.

Roberts, G. O., and J. S. Rosenthal. 2001. Infinite hierarchies and prior distributions. Bernoulli, 7: 453–471. SAFMC 2006. SEDAR Stock Assessment for Large Coastal Sharks. Panama City, FA.

Royall, R. 1997.Statistical evidence: a likelihood paradigm. Chapam and Hall, London.

Shark Angels 2011.Uses for sharks. Shark Angels Organitation. Available: www.harkangels.org (November 2013).

Simpfendorfer, C. A., M.R. Heupel, W.T. White, and N.K. Dulvy. 2011. The importance of research and public opinion to conservation management of sharks and rays: a synthesis. Marine and Freshwater Research 62, 518–527.

Stevens, J. D. 1984. Biological observations on sharks caught by sport fishermen off New South Wales. Australian Journal of Marine and Freshwater Research 35: 573-590.

Stevens, J. D., and J. M. Lyle. 1989. Biology of three hammerhead sharks (*Euphyra blochii, Sphyrna mokarran,* and *Sphyrna .lewini*) from northern Australia. Australian Journal of Marine and Freshwater Research 40: 129-146.

Techera, E.J., Klein N. (2011) Fragmented governance: reconciling legal strategies for shark conservation and management. Mar Policy 35: 73–78.

Tolentino, V., Cabello, M.G., Linares, F.A. and C.R. Mendoza. 2008. Age and growth of the scalloped hammerhead shark, *Sphyrna lewini* (Griffith & Smith, 1834) from the Southern coast of Sinaloa, México. Hidrobiológica 18: 31-40.

Tolentino, V. A., and C. R. Mendoza. 2001. Age and growth for the scalloped hammerhead shark, *Sphyrna lewini* (Griffith and Smith, 1834) along the central Pacific coast of Mexico. Ciencias Marinas 27: 501–520.

De Valpine, P., and A. Hastings. 2002. Fitting population models incorporating process noise and observation error. Ecological Monographs **72**:57–76.

Wade P. R. 1999. A comparison of statistical methods for fitting population models to data. Marine mammal survey and assessment methods: 249– 270 (A. A. Balkema, Ed.). Proceedings of the symposium on marine mammal survey and assessment methods, Seattle, Washington, U.S.A

Walker, T. I. 1998. Can shark resources be harvested sustainably? A question revisited with a review of shark fisheries. Marine and Freshwater Research, 49(7): 553–572.

White, W. T., C. Bartrin, and I. C. Potter. 2008. Catch composition and reproductive biology of *Sphyrna lewini* (Carcharhiniformes, Sphyrnidae) in Indonesian waters. Journal of Fish Biology 72: 1675-1689.

WildEarth Guardians and Friends of Animals. 2011. Petition to list the scalloped hammerhead shark (*Sphyrna lewini*) under the U.S endangered species act. Pag 33.

Tables

Table 1.1: Taxonomic classification of scalloped hammerhead shark.

Kingdom	Animalia
Phylum	Chordata
Class	Chondrichthyes
Subclass	Elasmobranchii
Order	Carcharhiniformes
Family	Sphyrnidae
Genus	*Sphyrna*
Species	*S.lewini*

Table 1.2: Summary of studies describing some aspects of the biology of *Sphyrna lewini*.

Location	Sex	Maximun TL	TL at maturity	Age at maturity (years)	Gestation (months)	TL at birth (cm)	Lither size	Parturition	Longevity	Reference
Hawaii	F	309				40-50	13-51	Year round (Peak in summer)		Clarke(1971) Duncan and Holland(2006)
	M	272								
Southern Africa	F	307	212			45-50	30	Summer		Bass et al.(1975)
	M	295	140-165							
Eastern Indian	F	346	212							Compagno(1984)
	M	301	140-165			42-55	15-31			
New South Wales	F									Stevens(1984)
	M	219-281								
Gulf of California*	F	296	217	7.4						Klimley(1987)
	M	244	163	3.6						
Gulf of Mexico	F	329 (all)	250	15						Branstetter (1987)
	M	329(all)	180	10	12	49	>30			
Northeastern Taiwan	F	331	210	4.1					14	Chen et al.(1988,1990)
	M	301	198	3.8	10	>45	12-38	Summer	11	
Northern *	F	346	200	9.5						Stevens &Lyle(1989)
Australia	M	301	140-160	4.7-6.7	9-10	45-50	13-23	October to January		
North-west Atlantic						38-45	20			Castro(1993)
Senegal						37-52	18-22	Summer		Capape et al.(1998)
Northern Brazil	F									Lessa et al.(1998)
	M		<150			40-50				
Spain	F	320								Buencuerpo et al.(1998)
	M	280								
Northeastern Brazil*	F	273	240	15.2						Hazin et al.(2001)
	M	321	180-200	6.3-8.1	10	>38	2-21	Summer		
Pacific Mexico		335.6	223							Tolentino & Mendoza(2001)
		244.3	170							
North-west Atlantic**	F	312.9 (234 FL)							30.5	Piercy et al.(2007)
	M	303.8 (241 FL)							30.5	

Location	Sex	Maximun TL	TL at maturity	Age at maturity (years)	Gestation (months)	TL at birth (cm)	Lither size	Parturition	Longevity	Reference
South Africa (E)*	F		184	11			10			Dudley & Simpfendorfer (2006)
	M		161	11						
LIS(FL)	F							Spring/ Summer	35-56.2	Adams and Paperno (2007)
	M									
Mexico (Southern cost Sinaloa)	F	280	204	6.5		45-55		Summer		Tolentino et al. 2008
	M	281	170	4						
Indonesia*	F	316.8	228.5	6.5	8			Year round (peak in Oct-Nov)		White et al.(2008)
	M	239.9	175.6	4		39-57	14-41			
Australia (NSW-SE)	F	260	195-260							Macbeht et al.(2009)
	M	299	200							
Mexico (SW Pacific)*	F		220	7.6		>51	14-40	Summer		Bejarano-Alvarez et al.(2011)
	M		180	4.4						
Australia (NE)						500	1-25	Spring/ Summer		Noriega et al. (2011)
Australia (E):	M							Year round (peak in late Spring/Sum)	46.5-56.3	Harry et al. (2011)
	F									
Tropics	F		>128							
	M	197		5.7						
Temperate	F	260		8.9						
	M	290								
Southern Brazil	F	217							31.5	Kotas et al.(2011)
	M	234							29.5	

*Age at maturity estimates calculated by Miller et al. 2013.

**FL: Fork length

Table 1.3: Summary of maximum age observed, age at maturity, and ageing method for the scalloped hammerhead shark in different world regions.

Author	Method Annual	Method Biannual	Maximum age observed(years)	Age at maturity(years)
Branstetter(1987) (Gulf of Mexico)	X			Female: 15 Male: 9-10
Chen et al. (1990) (NE Taiwan)		X	Female: 14 Male: 10.6	Female: 4.1 Male: 3.8
Tolentino et al. (2008) (Pacific Mexico)		X	Female: 12.5 Male: 11	Female: 6.5 Male: 4
Piercy et al. (2007) (NW Atlantic)	X		Female: 30.5 Male: 30.5	
Harry et al. (2011)* (E Australia, temperate)	X		Female: 15 Male: 21	Male: 8.9
Kotas et al. (2011) (S Brazil)	X		Female: 31.5 Male: 29.5 (Longevity 55 years)	

* Estimates calculated by Miller et al. 2013.

Table 1.4: National Marine Fisheries Services shark management unit (NMFS, 2006).

Management Unit	Sharks Species Included
Large Coastal Sharks (11)	sandbar, silky, tiger, blacktip, bull, spinner, lemon, nurse, smooth hammerhead, scalloped hammerhead, great hammerhead
Pelagic Sharks (5)	shortfin mako, thresher, oceanic whitetip, porbeagle, blue
Small Coastal Sharks (4)	Atlantic sharpnose, blacknose, finetooth, bonnethead
Prohibited species (19)	whale, basking, sand tiger, bigeye sand tiger, white, dusky, night, bignose, Galapagos, Caribbean reef, narrowtooth, longfin mako, bigeye thresher, sevengill, sixgill, bieye sixgill, Caribbean sharpnose, smalltail, and Atlantic angel sharks

Table 1.5: Summary of current shark regulations (SEDAR 11, NMFS 2006).

<table>
<tr><td colspan="5">PROHIBITED SPECIES</td></tr>
<tr><td colspan="5">The following sharks cannot be kept commercially or recreationally. Whale, basking, sand tiger, bigeye sand tiger, white, dusky, night, bignose, Galapagos, Caribbean reef, longfin mako, bigeye thresher, sevengill, sixgill, biegeye sixgill. Caribbean sharpnose, smalltail, and Atlantic angel sharks. There is a mechanism in place to add or remove species, as needed, via rulemaking.</td></tr>
<tr><td colspan="5">COMMERCIAL REGULATIONS</td></tr>
<tr><td>Management Unit</td><td>Species that can be retained</td><td>Quota (unt dw)</td><td>Regional Quotas</td><td>Authorized Gears</td></tr>
<tr><td>Large Coastal Sharks
-directed commercial retention limit of 4,000 lb dw per trip
-incidental retention limit</td><td>Sandbar, silky, tiger, blacktip, bull, spinner, lemon, nurse, smooth hammerhead, scalloped hammerhead, great hammerhead</td><td>1.017</td><td>NA = 7%
SA = 41%
GM =51%</td><td rowspan="5">Pelagic or Bottom Longline; Gillnet; Rod and Reel; Handline; Bandit Gear</td></tr>
<tr><td rowspan="3">Pelagic Sharks
-no directed retention limit
-incidental retention limit</td><td>Shortfin mako, thresher, oceanic whitetip</td><td>488</td><td rowspan="3">None</td></tr>
<tr><td>Porbeagle</td><td>92</td></tr>
<tr><td>Blue</td><td>273</td></tr>
<tr><td>Small Coastal Sharks
-no directed retention limit
-incidental retention limit</td><td>Atlantic sharpnose, blacknose, finetooth, bonnethead</td><td>454</td><td>NA = 3%
SA = 87%
GM =10%</td></tr>
<tr><td colspan="5"><u>Additional remarks:</u>
- All sharks not retained must be released in a manner that ensures the maximum probability of survival
- Finning is prohibited for all sharks no matter what species
- Fishing seasons: January 1 to April 30; May 1 to August 30; September 1 to December 31
- Fishing regions: NA = Maine through Virginia; SA = N. Carolina through East Florida and Caribbean; GM = Gulf of Mexico
- Quota over and underharvest adjustments will be made for the same season the following year; no reopening that season
- Count state landings after Federal closure against Federal quota
- Time/area closure for vessels with bottom longline gear on board: January through July between 35” 41’N to 33” 51’N and west of 74” 46’W, roughly following the 60 fathom</td></tr>
</table>

contour line, diagonally south to 76” 24’W and north to 74” 51’W

- Vessel Monitoring Systems required for all gillnet vessels during right whale calving season and from January through July for all vessels with bottom longline gear on board between 33”00’N and
- 36” 30’N
- Limited access; Exempted Fishing Permit (EFP) requirements; Display permits for collection for public display
- Observer and reporting requirements
- For incidental limited access permit holders: 5large coastal sharks per trip; a total of 16 pelagic or small coastal sharks(all species combined) per vessel per trip
- Vessels with bottom longline gear on board must: (1)have non-stainless steel corrodible hooks; (2) have a dehooking device (when approved), linecutters, and dipnet on board; (3) move 1nmi after an interaction with a protected species; and (4) post sea turtle handling and release guidelines in the wheelhouse

RECREATIONAL REGULATIONS

Management Unit	Species that can be kept	Retention Limit	Authorized Gear
Large Coastal, Pelagic, and Small Coastal Sharks	LCS: Sandbar, silky, tiger, blacktip, bull, spinner, lemon, nurse, smooth hammerhead, scalloped hammerhead, great hammerhead Pelagic: shortfin mako, thresher, oceanic whitetip, porbeagle, blue SCS: Atlantic sharpnose, blacknose, finetooth, bonnethead	1 shark per vessel per trip (all species) with a 4.5 feet fork length minimum size; allowance for 1 Atlantic sharpnose and 1 bonnethead per person per trip (no minimum size)	Rod and Reel; Handline

Additional remarks:
Harvested sharks must have fins, head, and tail attached (can be bled and gutted if tail is still attached).

Table 1.6: Status of scalloped hammerhead shark subpopulations according to the IUCN (left side) and the ESA (right side).

IUCN	**ESA (CITES)**
Eastern Central &Southeast Pacific (EN)	Eastern Pacific DPS (Endangered)
Western Indian Ocean (EN)	Central Pacific DPS
	Indo-West Pacific DPS(Threatened)
Eastern Central Atlantic (VU)	Eastern Atlantic DPS (Endangered)
Northwest and Western Central Atlantic (EN)	Northwest Atlantic & Gulf Mexico DPS
Southwest Atlantic (VU)	Central & Southwest Atlantic DPS (Threatened)

Figures

Figure 1.1: Chondrichtyan species assessed globally and their status by IUCN (Modified from Camhi et al. 2009).

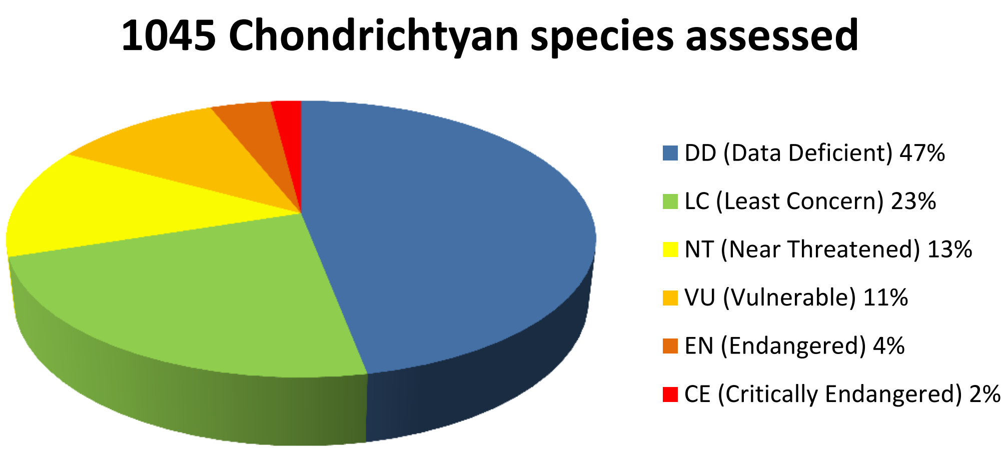


Figure 1.2: Main threats for Elasmobranchs (Modified from Ferreti et el. 2010).

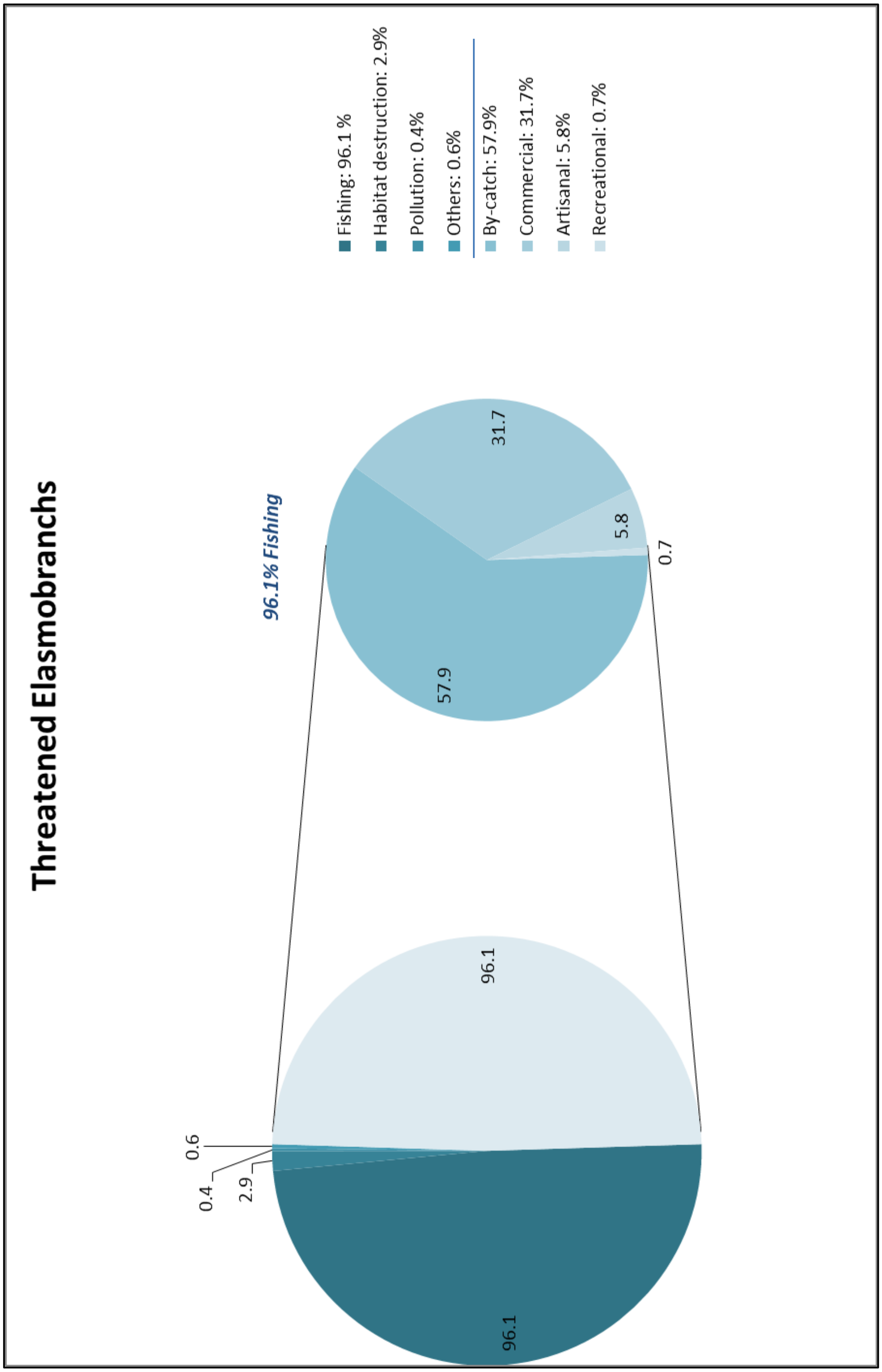


Figure 1.3: Global distribution of *Sphyrna lewini* (Plotted based on IUCN, 2013).

Chapter 2: Comparing the influence of different statistical paradigms in the scalloped hammerhead shark stock assessment for the western North Atlantic Ocean

Abstract

Past studies on scalloped hammerhead sharks in the western North Atlantic Ocean have agreed that the population has decreased; however, different researchers have provided diverse results in the rate or magnitude of decline. We used three different statistical paradigms (frequentist, likelihood and Bayesian) to assess the influence of these statistical estimators on the values of the key parameters (*r*, growth rate; *K*, carrying capacity; depletion, F_{MSY} , fishing levels that would sustain maximum yield; and N_{MSY}, abundance at maximum sustainable yield) of the logistic surplus production model (only measurement error considered). The estimates of the key parameters varied considerably from one paradigm to another. In the three paradigms tested, the population of scalloped hammerheads in the terminal year of the model was overfished (from 19% in Bayesian to 35% in frequentist approach), and overfishing was happening in two of them (except Bayesian one). This study showed that estimator selection influences the results of the surplus production model and therefore, the value of the target management points. Although the depletion results didn't vary largely (from 0.09 to 0.17), they may be enough to cause different changes in the predator-prey communities, and therefore they would imply different management strategies. While the use of Bayesian methods could seem risky because it is the only one that found the fishery status healthy, we recommend Bayesian estimator because: (1) we didn't have to fix unknown parameters when we used it (as in frequentist case), (2) the results estimated were credible (not as when we used likelihood estimator), (3) it accounts uncertainty of the data,

(4) it allows incorporation of informative priors, and (5) it provides as the result a posterior probability instead of a point estimate.

Keywords: *Sphyrna lewini*, parameters estimation, Bayesian approach, likelihood, observation error.

Introduction

Most sharks have late age of maturity, slow growth and low fecundity, and it causes the low resilience to even low levels of fishing. Thus, these features combined with the shark high by-catch in other fisheries have led to a large number of threatened shark populations (Musick et al. 2000). *Sphryna lewini* is a highly migratory shark species which is globally distributed, existing in diverse subpopulations around the world (IUCN 2013; Miller etal.2013; Table 2.1). They live in coastal and adjacent pelagic water in temperate and tropical seas (Compagno, 1984). Their intrinsic biology and the direct and indirect fisheries of this species are causing their overexploitation (Musick et al. 2000). *Sphyrna lewini* is managed within the Large Coastal Shark category in U.S waters (LCS, Table 2.2). It is included with another two species of hammerhead shark, *S.zygaena* and *S.mokarran*, smooth and great hammerhead shark respectively. Although the last assessment conducted by SEDAR (Southeast Data, Assessment, and Review 2006) estimated that the LCS complex was not overfished nor experiencing overfishing, the NMFS reported that the scalloped hammerhead shark stock was still overfished and experiencing overfishing based on Hayes et al. results (2009). Stock assessments of sharks often have had to focus on complexes because of the lack of species-specific data (NMFS 2006; Jiao et al. 2011).However, the assessment to the entire large coastal shark as a complex can mask information about the state of single species. This study assessed the scalloped hammerhead shark stock by itself using for first time Bayesian methods, which allowed comparing different statistical approaches (frequentist, likelihood and Bayesian) with the same kind of error (measurement error). We just used *S.lewini* data because great and smooth hammerheads have few abundance indices available and catch data are of questionable quality (Jiao et al. 2011, Figure 2.1).

All past studies of scalloped hammerhead sharks in the western North Atlantic Ocean agreed that the population has decreased (Baum et al. 2003; Burgess et al. 2005;Baum et al. 2005, Myers et al. 2007; Hayes et al. 2009); however, different researchers have provided diverse results in the rate or magnitude of decline. Based on the fact that the most current stock assessments of scalloped hammerhead sharks were using frequentist estimator, there was a need to determine the utility of different paradigms.

The goal of this study was to determine the utility of three different paradigms (frequentist, likelihood and Bayesian) when limited data are available, and compare the influence of these statistical estimators in the outcomes of the commonly used logistic surplus production model (only measurement error is considered). More specifically, we compared the confidence or credible interval of the parameter estimates *r, K,* and the biological reference points (F_{MSY}, fishing levels that would sustain maximum yield, and N_{MSY}, abundance at maximum sustainable yield) among the diverse cases tested.

Methods

Data

The population data used includes the data from New Jersey to the Caribbean, the Northwest and Western Central Atlantic subpopulation (IUCN 2013). This subpopulation has been shown to be genetically different from the others subpopulations in the Atlantic Ocean (Chapman et al. 2009). Since 1981, annual catch data and relative abundance indices of scalloped hammerhead sharks were recorded by NMFS (Table 2.3 and Figure 2.1). There are catch data from both recreational boats and commercial boats. Furthermore, discards from an observer program (the pelagic longline observer program, PLLOP) was considered in the total catch. There are 8 different relative abundance time series available for *Sphyrna lewini* (Figure 2.1, Table 2.4), the NMFS Mississippi bottom longline shark survey (NMFS-LL-SE; Ingram et al. 2005), the NMFS Panama City gillnet shark survey (PCGN; Carlson and Bethea 2005), the University of North Carolina longline survey (NCLL; Schwartz et al. 2007), the commercial shark fishery observer program (CSFOP; Cortés et al. 2005), the shark drift gillnet observer program (GNOP; Carlson et al. 2005), the pelagic longline observer program (PLLOP; Beerkircher et al. 2002), the Georgia Coastspan longline and trawl surveys (GACP; McCandless and Belcher, 2007), and the NMFS Longline Northeast (NMFS LL NE; Natanson 2007). However, this study followed the SEDAR recommendations (NMFS 2006) in selecting the relative abundance indices and used only 6 of these series (NMFS-LL-SE, PCGN, NCLL, CSFOP, GNOP, and PLLOP). A special data workshop has been conducted to discuss and recommend the data usability. Furthermore, Hayes (2008) showed that model sensitivity among six or eight indices was minimal. Therefore, the abundance indices that were not included in the base scenario are: GACP, given the short time series and large variance, and NMFS LL NE, due to the few years and high variance in the data. Before using these catch rate data, a standardization technique is required (Hilborn and Walters, 1992) and this standardization on hammerhead shark catch rate can be found in NMFS (2006).

Although there are some uncertainties related to the data that may cause uncertainty in the analysis of the population, we assumed that the data were accurate. However, the validity of historic catch and by-catch data may be questionable. Historic catch data may be misreported and misidentification at the species level (due to subtle morphological differences among the species of hammerhead sharks) could have happened (IUCN, 2013). Moreover, the relative abundance indices start in the early 1990s, while catch records start in 1981. Hayes (2008) tested catch uncertainty but the results had little changes. Lastly, most of the relative abundance indices are based on surveys that cover only small geographic areas, and not all areas are represented. Being *Sphyrna lewini* a highly migratory species, the small geographical area sampled could have a significant effect on our results. Hayes (2008) also checked this issue and the population status was more pessimistic when he weighted the abundance indices by the inverse of the variance. Although these uncertainties were considered, our work just focused on dealing with the uncertainty in the relative abundance indices when different statistical paradigms were used in the surplus production model.

Model

The surplus production model (Ricker 1975) was used to model the dynamics of the stock abundance (Equation 1). It is generally employed in fisheries and ecology because of its simplicity and moderate data requirements (May et al 1979; Hilborn and Walters 1992; Jiao et al. 2009a). Surplus-production models are used for shark stock assessments when catch and relative abundance data are the only information accessible or age-structure data are absent or of low quality (Prager 1994; Babcock and Pikitch 2001; Cortés 2002; Cortés et al. 2002; NMFS 2006; NMFS 2007). A surplus production model can provide similar information for management as when age-structured models are used (Ludwig and Walters 1985; Prager 1994; Haddon 2001). In this case, we used the logistic surplus-production model (Equation 2, Schaefer, 1954).

The change in numbers of a population over time (t) is described by the difference equation:

$$N_{t+1} = N_t + G_t - C_t \qquad \text{(Equation 1)}$$

where N_t is the population abundance in year t, G_t the production function of the population in year t, and C_t the total catch in year t. The production curve functions are described by:

$$G_t = rN_t(1 - N_t / K) \qquad \text{(Schaefer Model, Equation 2)}$$

where K is the carrying capacity (or virgin biomass) and r is the intrinsic population growth rate. The parameter r is representative of the intrinsic productivity of a population and also a direct determinant of its resilience to fishing. The surplus production model assumes that:

(1) r is constant in the species life, don't distinguish between immature and mature individuals (as aged structured model).
(2) There are no species interactions or environmental factors that affect the population.
(3) Fishing and natural mortality take place simultaneously.
(4) The abundance indices are proportional to population size. This model doesn't take into account the changes in fishing equipment or vessel efficient and q (catchability coefficient) is considered constant over time.
(5) There is no time lag in compensation, i.e., immediate response in the rate of population growth to changes in population abundance (Holden 1977).
(6) All indices are equally weighted (for example, not look at geographical coverage).
(7) Catch and effort statistics are accurate.

Parameters of management implications

To know the status of a fishery stock, one needs to compare an indicator reference point (e.g. current population size, N) with a management reference point (N that maximum sustainable yield) (Jiao et al. 2009). The parameters of management implication that we used to report the current stock status of *Sphyrna lewini* are: MSY, N_{MSY}, F_{MSY}, and percentage of depletion, i.e., the percentage of virgin stock that has been captured (N_t /K). When logistic population growth is used, N_{MSY} is equal to $K/2$ and F_{MSY} is $r/2$.

We calculated the probability that the estimated ratio of fishing mortality F relative to F_{MSY}, F/ F_{MSY} (fishery status), was greater than 1 [P(F> F_{MSY})], as an estimate of overfishing. The probability that the estimated population size relative to N_{MSY}, N/ N_{MSY} (population status), was smaller than 1 [P(N< N_{MSY}], was also estimated to evaluate the probability of the population being overfished. The estimates of these parameters were compared among different models (Figure 2.2). We presented the results of F/F_{MSY} and N/N_{MSY} in a probabilistic way and we stated the distribution of MSY to incorporate the uncertainty of these estimates caused by the data and model deficiencies.

Types of estimators used for the measurement error

The surplus production model is usually comprised of one process equation and one or more observation equations. An estimator has to be chosen to fit this model to the observed data. There are 3 kinds of estimators based on the types of the uncertainty considered: in the observation equation (measurement error), in the process equation (process error) or in both equations (process-measurement error). Here, we used measurement error because this estimator was found to be robust (Punt 1992, Punt and Hilborn 1997; de Valpine and Hastings. 2002; Hilborn and Walters 1992; Polacheck at al. 1993; He, 2010) and gave us the opportunity to compare the three paradigms, frequentist, likelihood, and Bayesian, at the same time.

Observation (or measurement) error is the difference between changes in the true population abundance and change in the abundance indices. Because population size cannot be observed directly, an observation model is used to relate population size (N_t) to a variable that is directly related to stock abundance. The observational model usually used can by written as:

$$I_{i,t} = q_i N_t e^{\varepsilon_i} \quad \text{(Equation 3)}$$

This model assumes that catch per effort is a linear function of abundance (Punt and Hilborn 1997). Moreover, we used a lognormal error structure, which is usually assumed in the surplus production model, because avoid that an observed quantity can be negative (Punt and Hilborn 1997; Quinn and Deriso 1999). The observation equation (equation 3) assumed this kind of error structure (multiplicative error structure) where $I_{i,t}$ is the abundance index *i* at time t (*i* indicate the different fisheries), q_i is the catchability coefficient for the index *i*, and ε_i is the error in the index *i*. Thus, we can rewrite the observation equation 3 as:

$$\log(I_{i,t}) = \log(q_i N_t) + \varepsilon_{i,t} \quad \text{(Equation 4)}$$

With the assumption that each *I* is an independent random variable, the estimates of the model parameters can be obtained by optimizing an objective function. We made two different objective functions (using likelihood and Bayesian approaches) and compared them with the frequentist function obtained by Hayes (2008; Table 2.5). Therefore, we worked with three statistical estimators to deal with the measurement error model.

Hayes (2008) used bootstrap to estimate the key parameters of the surplus production model and their uncertainty. Using the Least Squares criterion; he minimized the sum of the residual errors squares (SSR) in all the replicate samples ($\sum_i \sum_t (\log(I_{i,t}) - \log(q_i N_t))^2$). Their objective function was based on the assumption that index *I* is lognormally distributed; this way we can compare his objective function with our objective functions. We wanted to compare the influence of other two statistical estimators in the outcome of the surplus production model.

An alternative to the least squares approach is the maximum likelihood as criterion of quality of fit. In this case, parameters were selected when they maximized the probability density or likelihood (Haddon, 2001). The big advantage of this method is the residuals can follow any distribution. The likelihood of the parameter(s) θ is the product of the probability density function (pdf) values for each of the *n* observations X_i given the parameter(s) θ:

$$L(\theta) = \prod_{i=1}^{n} pdf(X_i \mid \theta) \qquad \text{(Equation 7)}$$

In our case, we maximized the likelihood function based on the assumption of lognormal distribution of the index *I:*

$$L(I \mid r, K, N_t, q_i, \sigma_i) \propto \prod_i \prod_t e^{-1/2\sigma_i^2 (\log I_{i,t} - \log(q_i N_t))^2} \qquad \text{(Equation 8)}$$

To quantify the uncertainty associated with a parameter estimate, we conducted likelihood profiling to get the likelihood ratio confidence interval (LRCI) of the parameters (Hilborn and Mangel 1997; Wade 1999; Jiao et al. 2009). Values of the parameter close in likelihood to the MLE are used to calculate the LRCI. A *k*-value equal to 6.82 is used because it is analogous to a 95% confidence interval in a likelihood ratio chi-square test (Equation 9; Jiao et al. 2009).

$$[\ L(\text{data}|\theta_{MLE}) \ /\ L(\text{data}|\theta_0)\ ] = k \qquad \text{(Equation 9)}$$

When a Bayesian approach was used to estimate parameters, specification of prior distributions on all the unknown parameters, was needed (Berger 1985; Gelman et al. 2004). According to Bayes' law:

$$p(\theta \mid data) \propto L(data \mid \theta)\, p(\theta) \\ = \prod_i \prod_t L(I_{i,t} \mid r, K, N_0, q_i, \sigma_i)\, p(r)\, p(K)\, p(N_0) \prod_i p(q_i) \prod_i p(\sigma_i) \qquad \text{(Equation 10)}$$

The Bayes' theorem uses likelihood [$L(\,data|\theta)$] and a prior distribution [$p(\theta)$] to calculate a posterior distribution from the observed data [$p(\theta|data)$]. Prior distributions of the parameters summarize the prior knowledge of these parameters (Berger 1985; McAllister and Kirkwood 1998; Gelman et al. 2004, Jiao et al. 2011; Equation 10). To reduce the impacts of prior information on parameter estimation, we used uninformative priors for all parameters except for *r* where we introduce prior knowledge (Chen and Fournier 1999).

$$r \sim N(0.061, 0.0996)$$

$$K \sim U(\max[catch],\ 35677)$$

$$q \sim U(0.0001,\ 3)$$

$$\sigma_i^2 \sim U(0.00001,\ 1)$$

The parameter *r* was assumed to follow a normal distribution with mean a_1 = 0.0661 and variance a_2 = 0.0996. These values are based on summarized information on the population growth rate of 80 shark species and stocks (Hoenig and Gruber 1990, Cailliet et al. 1992, Sminkey and Musick 1995, Smith et al. 1998, Cortes et al. 2002, Mollet and Cailliet 2002, Jiao et al. 2011). The carrying capacity, *K*, was assumed to follow a uniform distribution with lower bound equal to the maximum catch of scalloped hammerhead shark (carrying capacity never could be less than the maximum catch) and upper bound 35677($x10^3$), the estimated carrying capacity of large coastal shark (NMFS 2006).

When the Bayesian approach was used, Markov Chain Monte Carlo (MCMC) simulation was conducted to estimate parameters with uncertainty. The number of runs was 10,000 and before these runs, we discarded the burning period. The thinning interval was five. We checked three different methods to see when random draws had converged to the posterior distribution. We monitored the traces for key parameters, diagnosed the autocorrelation plot for key parameters and used Gelman and Rubins convergence diagnostic (Gelman and Rubin 1992, Su et al. 2001, Spiegelhalter et al.2004)

Because the model used in this study is really one model but with three different estimators, no quantitative model selection criteria such as AIC, BIC or likelihood ratio test were used to compare them. To compare the measurement error model with the three paradigms, we compared their parameter estimates and BRPs (biological references points) estimates by comparing the estimates of mean, and confidence or credible intervals (Table 2.5). We then discussed the appropriateness of the estimator in this case based on their data and results characteristics.

Results

When we compared the size of the confidence and credible intervals, we have to take into account that they are based on different statistical theories. When the frequentist approach is used, 95% confidence interval means that if we pick new data several times and we calculate confidence intervals each time, 95% of these confidence intervals contain the true value of the parameter. In frequentist terms, the parameter is fixed (cannot be considered to have a distribution of possible values as in Bayesian approach) and the confidence interval is random (as it depends on the random sample). In likelihood and Bayesian terms, we speak about degree of belief. The likelihood ratio confidence interval was based on the likelihood ratio of it and usually a ratio (exp(1.92)=6.82) of a normal distribution approximately is used, which indicated the degree of the support from the data at the MLE is 6.82 times of the support at the likelihood confidence intervals. A credible interval of 95% from Bayesian approach means that the probability that the value of the parameter is between the credible intervals values is 95%, given the observed data and our initial belief.

The three logistic models with different estimators (frequentist, likelihood and Bayesian) resulted in different values of the key parameters r and K, and depletion (N/K) (Table 2.5; Figure 2.3). On one side, the ranges of confidence intervals for the parameters from the frequentist and likelihood approaches were wider than the credible interval informing the Bayesian method. However, when we compared the length of the confidence and credible intervals, we have to consider that Bayesian estimator used an informative prior of r and K, which contributed to the overall posterior likelihood and influenced the credible interval of r and K to be smaller. On other side, Hayes (2008) fixed the initial depletion (N_0/K = depletion at initial population size) and therefore, he incorporated less uncertainty in the model. When likelihood estimator was used, N_0/K was calculated (not fixed) but this value was very wide and the likelihood ratio confidence interval was out of the range of it. The Maximum Likelihood Estimate (MLE) tended to be at $N_0/K=1$ (Figure 2.3). This indicated high uncertainty of the initial depletion of the stock based on the data available for scalloped hammerhead sharks and therefore, that the likelihood estimator didn't work well considering this source of uncertainty.

When MCMC simulation was conducted to estimate parameters with uncertainty, the three methods tested (monitoring the trace for key parameters, diagnosing the autocorrelation plot for key parameters, and Gelman and Rubin statistic) failed to show evidence against convergence of the MCMC algorithm.

Among the three models/estimators investigated, the population of scalloped hammerheads was currently (for 2005) overfished, and overfishing was occurring in two of the three approaches (Table 2.5, Figure 2.2). It means that stock size was below the population size that produces MSY and that the rate of fishing was greater than that associated with MSY, except for the Bayesian paradigm. The phase plot (Figure 2.2) compared the three different paradigms and, what we are showing is the mean in the frequentist case, the mode in the likelihood approach and the posterior mean for the Bayesian paradigm. We didn't show the confidence ellipses around the estimates for a direct and easy interpretation of the plot for all stakeholders. Bayesian approach was the most optimistic one based on the fisheries status (F_{2005}/F_{MSY} =83%), but the most pessimistic based on the population status (N_{2005}/N_{MSY}=19%). MSY, the largest sustainable catch that may be taken from this stock, was 10.4 ($x10^3$) and 10.3($x10^3$) according to frequentist and likelihood paradigms respectively, but it was 12.9($x10^3$) according to Bayesian approach (Table 2.5). There was a difference of around 2000 fishes. It is because Bayesian model estimated a bigger carrying capacity of the stock. The depletion value (N_{2005}/K) ranged from 0.17 to 0.09, which means that the population estimated in 2005 was at 9% to 17% of the carrying capacity estimated (Table 2.5; Figure 2.3). Although the estimated parameters were not all the same when the three estimators were used, the results were still similar.

Discussion

This study tried to determine the utility of different paradigms (frequentist, likelihood and Bayesian) when limited data are available (as in the case of scalloped hammerhead sharks) and compare the influence of these statistical estimators in the outcome of the surplus production model when only observation error was considered. We found as Wade (1999) that the outcome of the three models/estimators tested varied considerably. Our results strongly suggested that the choice of the statistical estimators influences the model outcome (key parameters estimates), at least for the *S.lewini* data. Our estimates were not all the same when the three estimators were tested. Although the results were close from each other, the credible and confidence intervals lengths varied considerably. Wade (1999) also found that points of estimates from each approach were similar, but intervals varied substantially. He pointed out that there are strengths and weaknesses in the three approaches tested, and the important thing is to be aware of it, and choose the one statistical inference which may be most appropriate for our study.

In our case, we suggest the use of Bayesian methods because allow us to develop a model closer to the reality, taking more uncertainty into account and getting reasonable values for the parameters. For Bayesian approach, we didn't fix the parameter N_0/K as in the frequentist case (because it is unknown), and the results for this parameter was reasonable (not like when used likelihood estimator). In this study, with the likelihood approach, the MLE showed that initial depletion value had high uncertainty. The high uncertainty of initial depletion indicated high uncertainty of other key parameters such as r, K and fishery and population status, because they were all highly correlated. This would also cause high uncertainty when frequentist approach is used because of the difficulty of finding the global maximum of the likelihood (Prager 1994). The high uncertainty of the initial depletion for *Sphyrna lewini*, could be likely caused by the high catch in year 1982(cause a lack of contrast data), and the overall declining trend of the catch and abundance indices. When frequentist or likelihood approaches are used, parameters such as N_0/K are often fixed because of the flat likelihood profile (with 95% likelihood ratio confidence interval out of the range of the parameters) as shown in Figure 2.3. Bayesian approach has advantage over frequentist or likelihood approaches; we didn't need to fix the parameters N_0/K to avoid the flat profile (Posada and Buckley 2004). Furthermore, the shape of the likelihood profile or the overall estimator when frequentist and likelihood approaches are used, are often ignored since the "best" estimates is often reported as MLE. This can be problematic when the distribution of the parameter is not normal, as in this case. Therefore, Bayesian estimates of the population and fishery status are more credible.

There are some sources of uncertainty about the catch data, that we didn't check in our study, however, they could have an effect in the key parameters estimated. We considered that all catch data are accurate, but it is known that there are illegal, unreported and unregulated catch (especially in historic data) that are not been taking into account in the assessments. We don't know if there was a change in misreporting the data over time and when it happened. The recreational catch system of reporting in the first few years was not well regulated and with problem in the identification of the different hammerhead sharks species. Moreover, recreational catches in some years were excessively large (around 1/3 of the carrying capacity; Table 2.3) and it could be because they were calculated extrapolating the fishing effort data. This also could be the explanation of having the same number of commercial catches in 1995 and 1996 (Table 2.3). *S .lewini* has a schooling behavior, and therefore, this high catch could be also due to the fact that fishermen found a schooling area. Furthermore, this aggregating behavior can affect the catchability coefficient (q) that we consider constant over time.

Although our model assumed that there was not delay due to growth and recruitment in the response of the population to fishing, we know it is not biologically true (Musick and Bonfil .2005). Delay-difference models should be used in the future to get more realistic biological results. If age-structured models are not available, Deriso delay-difference model (1980) or the simplified version of Cortés (2002) could be used.

This study showed that estimator selection influences the results of the surplus production model and therefore, the value of the target management points. Although the depletion results didn't vary largely (from 0.09 to 0.17), they may be enough to cause different changes in the predator-prey communities, and therefore they would imply different management strategies. The decreasing of an apex predator as *Sphyrna lewini*, have top-down effects on the ecosystem, being the most direct one, the increase of the scalloped hammerhead shark preys (Myers et al.2007). Our study suggest that the status of the scalloped hammerhead shark on the western North Atlantic Ocean is more depleted than Baum et al. (2003) and Hayes et al. (2009) found (89% and 83% respectively), but less than Myers et al (2007) suggest (98%, Table 2.5). Furthermore, the existence of a cryptic species (identical to *S.lewini*) from South Carolina to Brazil could have provoked an overestimation of the stock (Miller et al. 2013). This new knowledge should be taking into account to consider whether or not the NCLL abundance indices (the University of North Carolina longline survey) should be removed from the assessment. This index has the same geographical coverage that this cryptic species and it has a big influence on the assessment due to the long time series (Hayes 2008, Jiao et al. 2011).

When we looked at the fishery status among estimators, the differences caused by the estimator selection are more evident, going from not overfishing to overfishing. Although the use of Bayesian methods could seem risky because it is the only one that found the fishery status healthy, we recommend Bayesian estimator because: (1) we didn't have to fix unknown parameters when we used (as in frequentist case), (2) the results estimated were credible (not like when we used likelihood estimator), (3) it accounts uncertainty of the data, (4) it allows incorporation of informative priors, and (5)it provides as the result a posterior probability instead of a point estimate.

Bayesian results are more intuitive and useful for conservation management strategies (Wade 2000, Durban et al. 2000). Bayesian analysis allows us to compare multiple options at the same time (not as hypothesis testing) and it tells us how probable different values of the key parameter are (Wade 2000). Although many frequentist scientists have said that Bayesian inference problem is subjective, classic methods are not so objective how it is thought, and furthermore, they can led to erroneous conclusions (Senn 2003; Wade 2000). Finetti (1974) estimated that Bayesian inference would dominate over frequentist approach in 2020. Although his prediction could not come true at that time, it is a fact that Bayesian analysis have expanded to many diverse disciplines in the last times (Vallverdu 2008). Other scientists think that each approach contributes to develop the other one, and the debate of which paradigm is better, never is going to finish (Bayarri and Berger 2004).

References

Babcock, E. A., and E. K. Pikitch. 2001. Bayesian methods in shark fishery management. Shark News 13, 10-12.

Baum, J. K., D. G. Kehler, and R. A. Myers. 2005. Robust estimates of decline for pelagic shark populations in the northwest Atlantic and Gulf of Mexico. Science 299, 389-392.

Baum, J. K., R. A. Myers, D. G. Kehler, Worm, B., and Harley, S. J. 2003. Collapse and conservation of shark populations in the northwest Atlantic. Science 299, 389-392.

Bayarri, M. J and J. O. Berger. 2004. The interplay of Bayesian and frequentist analysis. Statistical Science 19: 58-80.

Beerkircher, L. R., C. J. Brown, and D. W. Lee. 2002. SEFSC pelagic observer program data summary for 1992-2000.NOAA Technical Memorandum NMFS-SEFSC-486. NOAA, Miami, Florida, USA.

Berger, J. O. 1985. Statistical decision theory and Bayesian analysis. Springer-Verlag, New York, New York, USA.

Carlson, J. K., I. E. Baremore, and D. M. Bethea. 2005. The directed shark gillnet fishery catch and bycatch, 2004. Sustainable Fisheries Division Contribution PCB-05-01.Sustainable Fisheries Division, Panama, City, Florida, USA.

Carlson, J. K., and D. M. Bethea. 2005. Standardized catch rates of large coastal sharks from a fishery-independent survey in northeast Florida. Southeast Data, Assessment and Review (SEDAR) 11, Large Coastal Shark Data Workshop LCS05/06-DW-12. Sustainable Fisheries Division, Panama City, Florida, USA.

Chapman, D. D., D. Pinhal, and M. S. Shivji. 2009. Tracking the fin trade: genetic stock identification in western Atlantic scalloped hammerhead sharks *Sphyrna lewini*. Endangered Species Research 9: 221-228.

Chen, C. T., T. C. Leu, S. J. Joung, and N. C. H. Lo. 1990. Age and growth of the scalloped hammerhead, *Sphyrna lewini*, in northeastern Taiwan waters. Pacific Science 44, 156–170.

Chen, Y., and D. Fournier. 1999. Impacts of atypical data on Bayesian inference and robust Bayesian approach in fisheries. Canadian Journal Fisheries and Aquatic Science 56: 1525–1533.

Chen,Y., and S. Montgomery. 1999. Modelling the dynamics of rock lobster, *Jasus verreauxi*, stock in NewSouthWales, Australia. Fishery Bulletin 97:25-38.

Chen, Y., Y. Jiao, and L.Chen. 2003. Developing robust frequentist and Bayesian fish stock assessment methods. Fish and Fisheries 4:105-120.

Compagno, L. J. V. 1984. FAO species catalog. Vol 4. Sharks of the world. An annotated and illustrated catalog of shark species known to date. Part 2. Carcharhiniformes. FAO Fisheries Synopsis 125: 655 pp.

Cortés, E. 2002. Stock assessment of small coastal sharks in the U.S. Atlantic and Gulf of Mexico. Sustainable Fisheries Division Contribution SFD-01/02-152. NOAA, NMFS, Southeast Fisheries Science Center, Panama City, FL, 133 pp.

Cortés, E., L. Brooks, and G. Scott. 2002. Stock assessment of large coastal sharks in the U.S.Atlantic and Gulf of Mexico. Sustainable Fisheries Division Contribution SFD-02/03-177. NOAA, NMFS, Southeast Fisheries Science Center, Panama City, FL, 133 pp.

Cortés, E., A. Morgan, and G. Burgess. 2005. Standardized catch rates of large coastal sharks from the commercial shark fishery observer program, 1994-2004. Southeast Data, Assessment and Review (SEDAR) 11, Large Coastal Shark Data Workshop LCS05/06-DW-17. Sustainable Fisheries Division, Panama City, Florida, USA.

De Valpine, P., and A. Hastings. 2002. Fitting population models incorporating process noise and observation error. Ecological Monographs **72**:57–76.

Durban, J. W., D.A. Elston, X. Lambin and, P. M. Thompson. 2000. A role for Bayesian inference in cetacean population assessment. Journal of Cetacean Research and Management 2, 117–123.

Deriso, R.B. 1980. Harvesting strategies and parameter estimation for an age-structured model. Canadian Journal of Fisheries and Aquatic Science 37: 268–282.

Finetti, B. D. 1974. Theory of Probability, volume 1-2.Wile John Wiley & Sons Ltd., Chichester.

Gelman, A., and D. B. Rubin. 1992. Inference from iterative simulation using multiple sequences (with discussion). Statistical Science 7:457–511.

Gelman, A., J. B. Carlin, H. S. Stern, and D.B. Rubin. 2004. Bayesian data analysis. Chapman and Hall, London, UK.

Haddon, M. 2001. Modelling and Quantitative Methods in Fisheries. Chapman & Hall/CRC Press, London/Boca Raton, 406 pp.

Hayes, C. 2008. Investigating single and multiple species fisheries management: stock status evaluation of hammerhead (*Sphyrna* spp.) sharks in the western North Atlantic and Gulf of Mexico. Thesis. Virginia Tech University, Blacksburg, Virginia, USA.

Hayes C., Y. Jiao, and E. Cortés. 2009. Stock assessment of scalloped hammerheads in the Western North Atlantic Ocean and Gulf of Mexico. North American Journal of Fisheries Management 29: 1406–1417.

He, Q. 2010. Investigating the performance of process observation-error-estimator and robust estimators in surplus production model: a simulation study. Thesis. Virginia Tech University, Blacksburg, Virginia, USA.

Hilborn, R., and C. Walters. 1992. Quantitative fisheries stock assessment: choice, dynamics, and uncertainty. Chapman and Hall, New York, New York, USA.

Hilborn, R. and M. Mangel. 1997. The ecological detective: confronting models with data. Princeton University Press.

Holden, M. J. 1977. Chapter 9: Elasmobranchs. In J. Gulland (ed.). Fish Population Dynamics, pp: 187–215. John Wiley and Sons, London.

Ingram, W., T. Henwood, M. Grace, L. Jones, W. Driggers, and K. Mitchell. 2005. Catch rates, distribution, and size composition of large coastal sharks collected during NOAA. Fisheries bottom longline surveys from the U.S. Gulf of Mexico and U. S. Atlantic Ocean. Southeast Data, Assessment and Review (SEDAR) 11, Large Coastal Shark Data Workshop LCS05/06-DW-27. Sustainable Fisheries Division, Panama City, Florida, USA.

IUCN 2013. IUCN Red List of Threatened Species. Available : www.iucnredlist.org. (September 2013).

Jiao, Y., and Y. Chen. 2004. An application of generalized linear models in production model and sequential population analysis. Fisheries Research 70: 367-376.

Jiao, Y**.,** K. Reid, T. Nudds, and E. Smith. 2009. Graphical evaluation of fishery status with a likelihood inference approach. North American Journal of Fisheries Management. 29:1106-1118.

Jiao, Y., E. Cortés, K. Andrews, and F. Guo. 2011. Poor-data and data-poor species stock assessment using a Bayesian hierarchical approach. Ecological Application 21: 2691–2708.

Ludwig. D., and C. Walters. 1985. Are age structured models appropriate for catch-effort data? Canadian Journal of Fisheries and Aquatic Sciences 40: 559-569.

May, R. M., J. R. Beddington, C. W. Clark, S. J. Holt, and R. M. Laws. 1979. Management of multispecies fisheries. Science 205: 267–277.

McAllister, M. K., and G. P. Kirkwood. 1998. Using Bayesian decision analysis to help achieve a precautionary approach to managing newly developing fisheries. Canadian Journal of Fisheries and Aquatic Sciences 55: 2642–2661.

McCandless, C. T., and C. N. Belcher. 2007. Standardized catch rates of small coastal sharks from the Georgia COASTSPAN and GADNR penaeid shrimp and blue crab assessment surveys. National Marine Fisheries Service, Southeast Fisheries Science Center, SEDAR 13-DW-27, Narragansett, Rhode Island.

Miller, M.H., J. Carlson, P. Cooper, D. Kobayashi, M. Nammack, and J. Wilson. 2013. Status review report: scalloped hammerhead shark (*Sphyrna lewini*). Report to National Marine

Fisheries Service, Office of Protected Resources. March 2013.131 pp.

Musick, J. A., and R. Bonfil .2005. Management techniques for elasmobranch fisheries. FAO fisheries technical paper 474.

Musick, J. A., G. Burgess, G. Cailliet, M. Camhi, and S. Fordham. 2000. Management of sharks and their relatives (Elasmobranchii). Fisheries 25: 9–13.

Myers, R. A., J. K. Baum, T. D. Shepherd, S. P. Powers, and C. H. Peterson. 2007. Cascading effects of the loss of apex predatory sharks from a coastal ocean. Science 315: 1846-1850.

Natanson, L. 2007. Catch rate information obtained from the NMFS northeast longline survey. National Marine Fisheries Service, Southeast Fisheries Science Center, SEDAR 11 LCS05/06-DW-33, Narragansett, Rhode Island.

NMFS, 2006. SEDAR 11. Stock assessment report: large coastal shark complex, blacktip and sandbar shark. US Department of Commerce, NOAA, NMFS, Highly Migratory Species, Silver Spring, MD, 387 pp.

NMFS. 2007. SEDAR 13. Stock assessment report: small coastal sharks. US Dept. Commerce, NOAA, NMFS, Highly Migratory Species Management Division, NOAA, Silver Spring, MD, 395 pp.

Prager, M. H. 1994. A suite of extensions to a nonequilibrium surplus production model. Fishery Bulletin 92: 374-389.

Polacheck, T., R. Hilborn, and A. E. Punt. 1993. Fitting surplus production models: comparing methods and measuring uncertainty. Canadian Journal of Fisheries and Aquatic Science 50: 2597-2607.

Posada, D. and T. R. Buckley. 2004. Model selection and Model averaging in Phylogenetics: Advantages of Akaike Information Criterion and Bayesian Approaches Over Likelihood Ratio Tests. Systematic Biology 53: 793-808.

Punt, A. E. 1992. Management procedures for Cape hake and baleen whale resources. Benguela Ecology Programme Report 23, 689 pp.

Punt, A. E., and R. Hilborn. 1997. Fisheries stock assessment and decision analysis: the Bayesian approach. Review in Fish Biology and Fisheries.7: 35–63.

Quinn, R. J., and R. B. Deriso. 1999. Quantitative Fish Dynamics. Oxford University Press, New York.

Roughgarden, J., and F. Smith. 1996. Why fisheries collapse and what to do about it. Ecology 93: 5078-5083.

Schwartz, F. J., C. T. McCandless, and J. J. Hoey. 2007. Trends in relative abundance for shark species caught during a UNC longline survey conducted between 1972 and 2005 in Onslow Bay, NC. SEDAR 13-DW-34-V2. Sustainable Fisheries Division, Panama City, Florida, USA.

Senn.S. 2003. Bayesian, likelihood, and frequentist approaches to statistics. A comparison of methods. Applied clinical trials 12(8):35-38.

Spiegelhalter, D. J., A. Thomas, N. Bestand, and D. Lunn. 2004. WinBUGS user manual (version 1.4.1). MRC Biostatistics Unit, Cambridge, UK.

Su, Z., M. D. Adkison, and B. W. Van Alen. 2001. A hierarchical Bayesian model for estimating historical salmon escapement and escapement timing. Canadian Journal of Fisheries and Aquatic Sciences 58:1648–1662.

Vallverdu, J. 2008. The false dilemma: Bayesian vs. frequentist. E-Logos: Electronic Journal for Philosophy: 1-26.

Wade P. R. 1999. A comparison of statistical methods for fitting population models to data. Marine mammal survey and assessment methods: 249– 270 (A. A. Balkema, Ed.). Proceedings of the symposium on marine mammal survey and assessment methods, Seattle, Washington, U.S.A

Wade P. R .2000. Bayesian Methods in Conservation Biology. Conservation Biology 14: 1308-1316.

Tables

Table 2.1.: Status of scalloped hammerhead shark subpopulations according to the IUCN (left side) and the ESA (right side).

IUCN	ESA (CITES)
Eastern Central &Southeast Pacific (EN)	Eastern Pacific DPS (Endangered)
Western Indian Ocean (EN)	Central Pacific DPS
	Indo-West Pacific DPS(Threatened)
Eastern Central Atlantic (VU)	Eastern Atlantic DPS (Endangered)
Northwest and Western Central Atlantic (EN)	Northwest Atlantic & Gulf Mexico DPS
Southwest Atlantic (VU)	Central & Southwest Atlantic DPS (Threatened)

Table 2.2: National Marine Fisheries Services shark management unit (NMFS, 2006).

Management Unit	Sharks Species Included
Large Coastal Sharks (11)	sandbar, silky, tiger, blacktip, bull, spinner, lemon, nurse, smooth hammerhead, scalloped hammerhead, great hammerhead
Pelagic Sharks (5)	shortfin mako, thresher, oceanic whitetip, porbeagle, blue
Small Coastal Sharks (4)	Atlantic sharpnose, blacknose, finetooth, bonnethead
Prohibited species (19)	whale, basking, sand tiger, bigeye sand tiger, white, dusky, night, bignose, Galapagos, Caribbean reef, narrowtooth, longfin mako, bigeye thresher, sevengill, sixgill, bieye sixgill, Caribbean sharpnose, smalltail, and Atlantic angel sharks

Table 2.3: Catches (in numbers of individuals) of *Sphyrna lewini* from 1981 to 2005. Blanks indicate missing data (NMFS 2006).

Year	Recreational	Commercial	Discards	Total
1981	5880	0		5880
1982	48138	1		48139
1983	20962	365		21327
1984	7003	0		7003
1985	44042	0		44042
1986	5321	0		5321
1987	6372	0	1228	7600
1988	4518	2	1674	6194
1989	6191	0	1389	7580
1990	18373	12	1151	19536
1991	8935	4	1221	10160
1992	7325	67	2257	9649
1993	21723	91	516	22330
1994	3886	301	368	4555
1995	3695	1479	567	5741
1996	882	1479	290	2651
1997	3905	1041	938	5884
1998	1083	642	234	1959
1999	545	386	344	1275
2000	6350	68	277	6695
2001	1112	1152	339	2603
2002	6113	1180		7293
2003	2859	2606		5465
2004	803	1351		2154
2005	803	2901		3704

Table 2.4: Summary of relative abundances indices for scalloped hammerhead sharks.

Index	Geographic coverage	Fishery Dependence	Units	Years	Reference
NMFS LL SE	South Atlantic and Gulf of Mexico	FI	Sharks per 10000 hook hours	1995-2005	Ingram et al.(2005)
PCGN	Northeastern Gulf of Mexico	FI	Gillnet: Sharks per net per hour	1996-2005	Carlson and Bethea (2005)
NCLL	Onslow Bay, North Carolina	FI	Shark per hook	1972-2005	Schwartz et al. (2007)
CSFOP	South Atlantic and Gulf of Mexico	FD	Sharks per 100 hooks per hour	1994-2005	Cortes et al. (2005)
GNOP	South Atlantic (Georgia, Florida) and Gulf of Mexico (Florida)	FD	Drift gillnet: Sharks per 107 m2 per hour	1994-2005	Carlson et al. (2005)
PLLOP	Western North Atlantic	FD	Sharks per 1000 hooks	1992-2005	Beerkircher et al. (2002)
GACP	Georgia estuaries	FI	Trawl	2000-2005	McCandless & Belcher (2007)
NMFS LL NE	South Atlantic (Florida to Delaware)	FI	Longline	1996-2005	Natanson(2007)

*FD: Fishery dependent survey/ FI: Fishery independent survey

Table 2.5: Key parameter values from the logistic surplus-production model under the three paradigms tested.

Reference Point	Least Squares (Hayes et al.2009)	Likelihood	Bayesian
r	0.29 (0.05-0.45)	0.31 (0.13-0.51)	0.37 (0.22-0.53)
K(1000s)	142 (116-260)	132 (105-273)	146 (103-230)
MSY(1000s)	10.4	10.3	12.9
F_{MSY}	0.15	0.16	0.19
N_{MSY}(1000s)	71	66.5	72.8
Depletion (N_t/K)	0.17	0.14	0.09
F_{2005}/F_{MSY}(%)	114	127	83
N_{2005}/N_{MSY}(%)	35	28	19

Figures

Figure 2.1: Indices of relative abundance of scalloped hammerhead sharks: the NMFS Mississippi bottom longline shark survey (NMFS-LL-SE; Ingram et al. 2005), the NMFS Panama City gillnet shark survey (PCGN,; Carlson and Bethea 2005), the University of North Carolina longline survey (NCLL; Schwartz et al. 2007), the commercial shark fishery observer program (CSFOP; Cortés et al. 2005), the shark drift gillnet observer program (GNOP; Carlson et al. 2005), the pelagic longline observer program (PLLOP; Beerkircher et al. 2002), the Georgia Coastspan longline and trawl surveys (GACP; McCandless and Belcher, 2007), and the NMFS Longline Northeast (NMFS LL NE; Natason 2007).

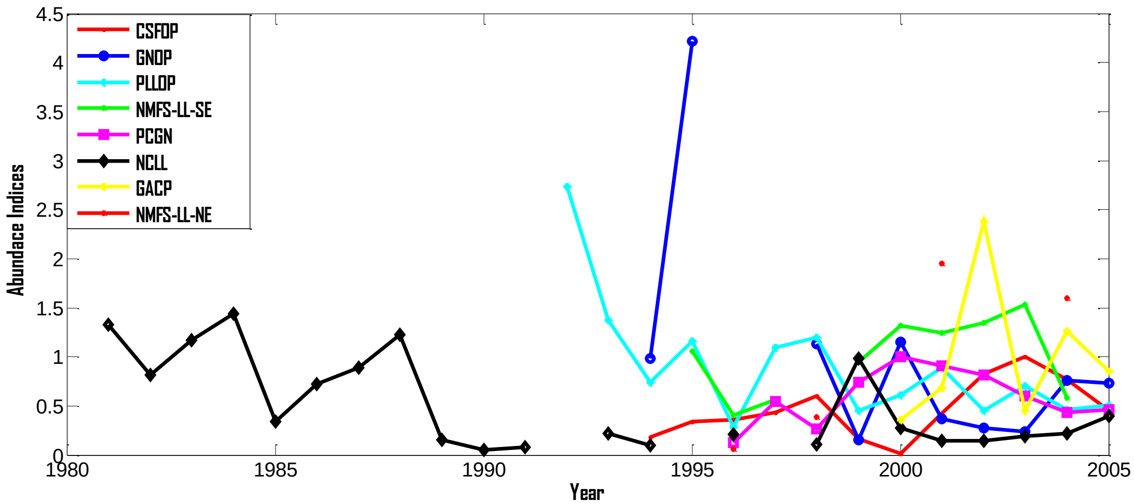


Figure 2.2: Phase plot for scalloped hammerhead sharks showed the population size in 2005 relative to N_{MSY} and fishing mortality in 2005 relative to F_{MSY} when the three paradigms (frequentist, likelihood and Bayesian) were used (NOTE: the safe quarter = bottom-right quarter).

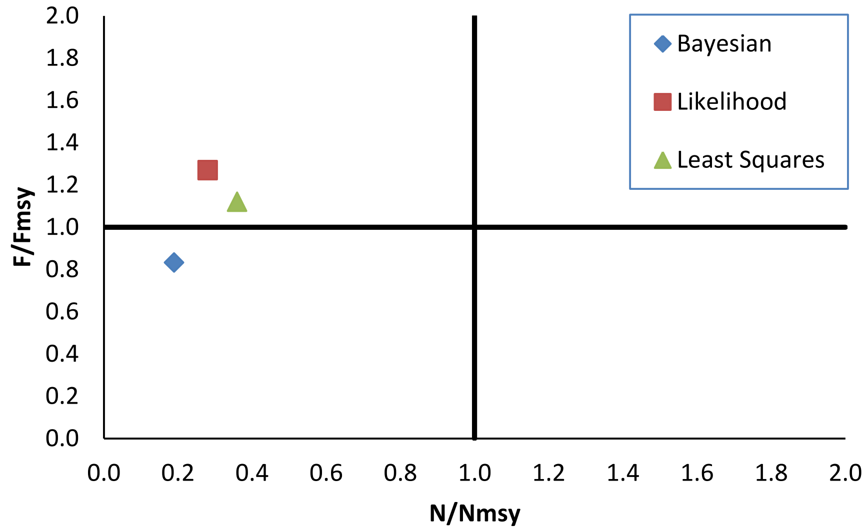
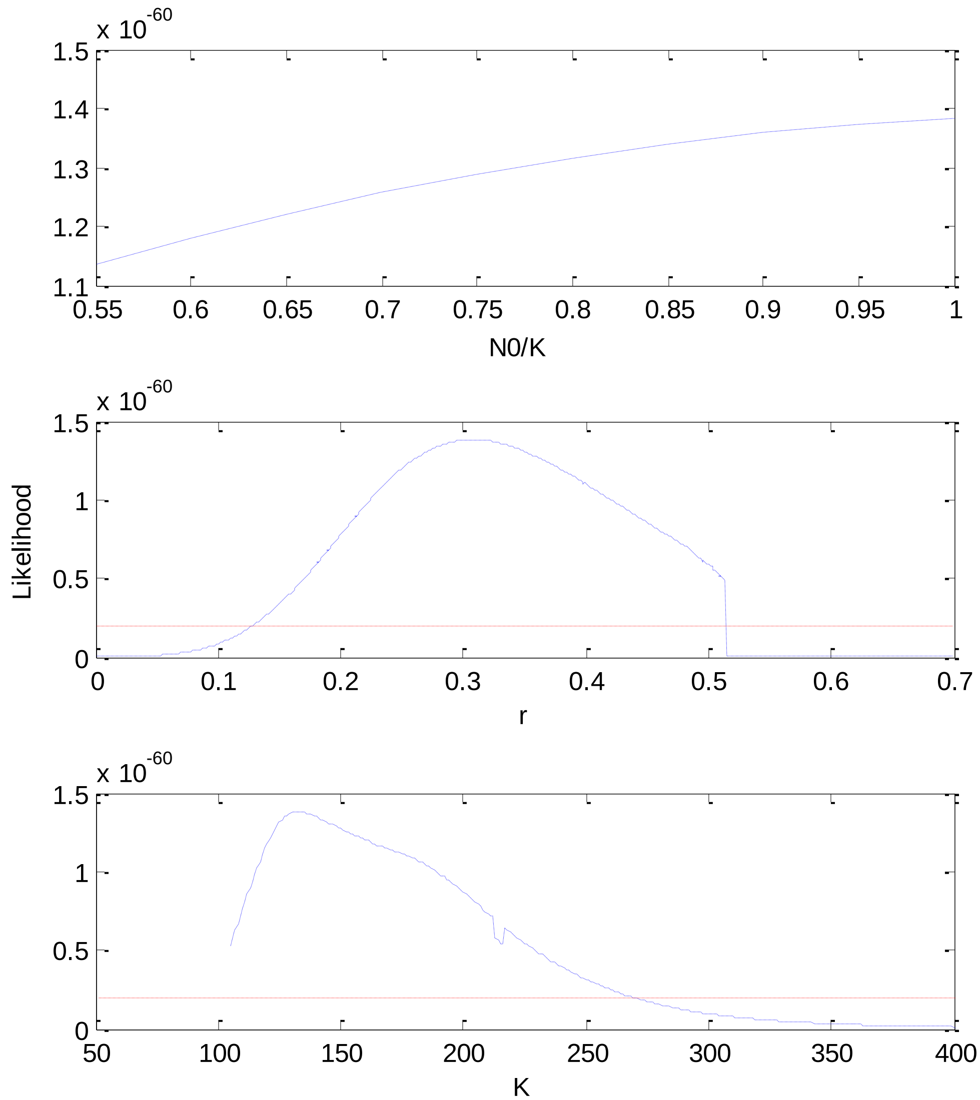
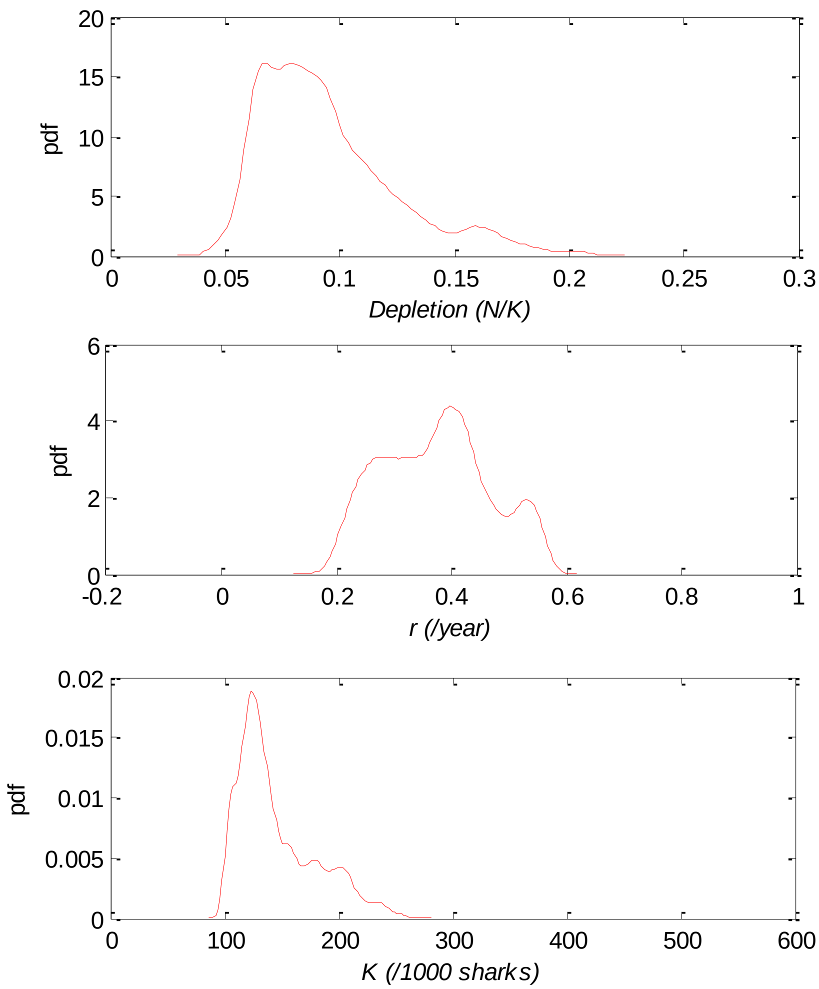


Figure 2.3: Estimates of the key parameters carrying capacity, growth rate, and % depletion using (a) likelihood paradigm (N0: initial population size) (b) Bayesian paradigm.

a)



(b)



20
15
10
5
0
pdf
0
0.05
0.1
0.15
0.2
0.25
0.3
Depletion (N/K)
6
4
2
0
pdf
-0.2
0
0.2
0.4
0.6
0.8
1
r (/year)
0.02
0.015
0.01
0.005
0
pdf
0
100
200
300
400
500
600
K (/1000 sharks)

Chapter 3: Comparing the influence of different Bayesian estimators in scalloped hammerhead shark stock assessment on the western North Atlantic Ocean

Abstract

Scalloped hammerhead shark populations have been assessed using a frequentist approach. A Bayesian approach has been increasingly used in recent years because of its ability to incorporate different sources of information and uncertainties. In this study, three Bayesian models were developed to introduce prior knowledge in the logistic surplus production model of *Sphyrna lewini* on the western North Atlantic Ocean and to compare different error considerations. The fishery was close to the limit of overfishing according to M1 and M3 (measurement error model and hierarchical model, respectively), but was above the limit from M2 (measurement-process model; $F/ F_{MSY} = 1.03$). The population was overfished in 2005 according to the three models tested, with M2 being the most conservative (N_{2005}/N_{MSY} ~0.14). When we looked to *Sphryrna lewini* population in 2005 regarding the virgin stock of the Atlantic and Gulf of Mexico coast of the USA, the depletion of the stock was equal to 91% according to M1, 93% according to M2, and 92 % according to M3. Based on the Deviance Information Criterion (DIC), Bayesian state-space surplus production model, hierarchical and not-hierarchically structured, fitted the data better than the model with only observation error considered. We suggest state-space (both hierarchical and non-hierarchical) Bayesian models for assessing of scalloped hammerhead shark or other fish stocks with poor data available to avoid mismanagement of the fisheries. Furthermore, based on this study and that there was very low evidence of recovery according with the last data available, we suggest prohibition of fishing for

this species because: (1) it is highly depleted (14% of its initial population), (2) the fishery status is very unstable over time (3) it has a low reproductive rate contributing to a higher risk of overexploitation, and (4) the easiness misidentification of the different hammerhead sharks (smooth, great, scalloped and cryptic species).

Keywords: *Sphyrna lewini*, surplus production model, Bayesian approach**,** measurement-process error, hierarchical Bayesian model

Introduction

Sphryna lewini is a highly migratory species, globally distributed, which is included in the IUCN Red List as Endangered species (IUCN, 2013). Their catches have been decreasing since the 80s on the western North Atlantic Ocean (Figure 3.1). Their intrinsic biology (late age of maturity, slow growth and low fecundity) and the direct and indirect fisheries for this species are causing their overexploitation. As a result, the U.S. National Marine Fisheries Service (NMFS) managed *Sphyrna lewini* as part of the Large Coastal Shark category since 1989 (LCS, Table 3.1). However, the assessment to the entire large coastal shark as a complex can mask information about the state of single species. Species-specific stock assessments are essential to really know the status of each species in the complex (NMFS 2006, Jiao et al. 2011). Although the last assessment conducted by SEDAR estimated that the LCS complex was not overfished nor experiencing overfishing (NMFS 2006), *S. lewini* could have a worse situation. Jiao et al. 2011 assessed the hammerhead shark complex and they concluded that *S. lewini* was probably overfished from 1983 to 2005 and overfishing occurred periodically from 1983 to 2005.

Past studies based only on scalloped hammerhead (Baum et al. 2003; Burgess et al. 2005;Baum et al. 2005, Myers et al. 2007; Hayes et al. 2009) have agreed that the population has decreased; however, different researchers have provided diverse results in the degree of decline. This study assessed the scalloped hammerhead shark population on the western North Atlantic Ocean using for first time Bayesian methods. This approach allowed incorporate diverse types of errors in the model and compare the influences of differrent statistical estimator in the final results of the logistic surplus production model. Furthermore, in the case of the *Sphyrna lewini*, multiple studies have derived different results on population growth rate, which encouraged us to consider multi-level priors (Jiao et al. 2009b).

Bayesian hierarchical analysis has been used to model data that are hierarchically structured, but it has also been used when multi-level priors are needed such as in this case. A simple Bayesian analysis uses a prior probability and the likelihood to compute the posterior probability (Bayes law: $p(\theta|data) \propto L(data|\theta)p(\theta)$; Hilborn and Mangel 1997, Jiao et al. 2011). However, in Bayesian hierarchical analysis, this prior probability depends on other parameters. Therefore, this prior probability is replaced by likelihood and the prior probability on the new introduced parameter or parameters. These kinds of priors are called multi-level priors, which have been proven to be more robust than single-level priors (Andrews et al. 1993; Roberts and Rosenthal 2001; Clark 2003).

The goal of this study was the assessment of the scalloped hammerhead shark stock (1) to determine the utility of different Bayesian approaches when limited data are available and (2) to compare the influence of error consideration (measurement and process-measurement error) in the final results. More specifically, DIC values and the credible intervals of the parameters estimates in the models, such as *r*, *K*, and the biological reference points (F_{MSY}, fishing levels that would sustain maximum yield, and N_{MSY}, abundance at maximum sustainable yield) were compared in the diverse Bayesian methods used.

Methods

Data

The scalloped hammerhead shark data used were from the Northwest and Western Central Atlantic subpopulation (IUCN 2013), which is genetically different from the others subpopulations in the Atlantic Ocean (Chapman et al. 2009). We used annual catch data (commercial, recreational and discards) and six abundance indices of the eight available to assess the scalloped hammerhead shark stock (Table 3.2, Table 3.3, and Figure 3.2). Discards were recorded by the pelagic longline observer program (PLLOP) and were considered in the total catch (Figure 3.3). The six indices used were: the NMFS Mississippi bottom longline shark survey (NMFS-LL-SE; Ingram et al. 2005), the NMFS Panama City gillnet shark survey (PCGN,; Carlson and Bethea 2005), the University of North Carolina longline survey (NCLL; Schwartz et al. 2007), the commercial shark fishery observer program (CSFOP; Cortés et al. 2005), the shark drift gillnet observer program (GNOP; Carlson et al. 2005), and the pelagic longline observer program (PLLOP; Beerkircher et al. 2002). Following SEDAR recommendations, we didn't used the abundance indices GACP (Georgia Coastspan longline and trawl surveys; McCandless and Belcher, 2007) , given the short time series and large variance, and NMFS LL NE(NMFS Longline Northeast; Natanson 2007), due to the few years and high variance in the data. Catch data were standardized before using them in the models (Hilborn and Walters, 1992) and this standardization can be found in NMFS (2006).

Models

The surplus production model (Ricker 1975) was used to model the dynamics of the stock abundance (Equation 1). It is widely employed in fisheries and ecology because of its simplicity and moderate data requirements (May et al. 1979; Hilborn and Walters 1992; Jiao 2009a). The surplus production model is usually composed of one process equation (equation 1) and one or multiple observation equations (equation 2):

$$N_{t+1} = N_t + G_t - C_t \qquad \text{(Equation 1)}$$

$$I_{i,t} = q_i N_t e^{\varepsilon_i} \qquad \text{(Equation 2)}$$

where N_t is the population abundance in year t, G_t the production function of the population in year t, and C_t the total catch in year t. The observation equation (equation 2) assumes a lognormal error structure (multiplicative error structure) where $I_{i,t}$ is the abundance index i at time t (i indicate the different fisheries, range from 1 to 6), q_i is the catchability coefficient for the index i, and ε_i is the error in the index i. Therefore, we can rewrite the Equation 2 as $\log(I_{i,t}) = \log(q_i N_t) + \varepsilon_{i,t}$.

We used the Logistic model (Schaefer model) as the production function, $G_t = rN_t(1 - N_t / K)$, because it is generally the one used in fisheries (Hilborn and Walter, 1992) and it had almost the same performance than Fox model (Hayes 2008). K is the carrying capacity (or virgin biomass) and r is the intrinsic population growth rate. The parameter r is representative of the intrinsic productivity of a population and also a direct determinant of its resilience to fishing. When a logistic population growth is used N_{MSY} (abundance at maximum sustainable yield), is equal to $K/2$ and F_{MSY} is $r/2$ (fishing levels that would sustain maximum yield). The biological references points, N_{MSY} and F_{MSY}, were used to determine the status of the stock.

An estimator has to be chosen to fit this model to the observed data. There are three kinds of estimators based on the types of the uncertainty considered: in the observation equation (measurement error), in the process equation (process error) or in both equations (process-measurement error). Here, we used measurement error in M1 and process-measurement error in M2 and M3 (see below) because these estimators were found to be more robust and less biased than the process error estimator (Punt 1992, Punt and Hilborn 1997; de Valpine and Hastings. 2002; Hilborn and Walters 1992; Polacheck at al. 1993; He, 2010).

This study compared the Bayesian hierarchically structured surplus production model to two traditional nonhierarchical surplus production models for scalloped hammerhead shark:

-Non-hierarchical model + measurement error (M1)

$$N_{t+1} = N_t + G_t - C_t$$

$$E(I_{i,t}) = q_i N_t e^{\varepsilon_i}$$

-Non-hierarchical model + measurement error + process error

(M2, Bayesian state-space surplus production model)

$$E(N_{t+1}) = N_t + G_t - C_t$$

$$E(I_{i,t}) = q_i N_t e^{\varepsilon_i}$$

-Hierarchical model (M3)

$$E(N_{t+1}) = N_t + G_t - C_t$$

$$E(I_{i,t}) = q_i N_t e^{\varepsilon_i}$$

$$G_t = rN_t(1 - N_t / K)$$

$$r \sim N(\bar{r}\,, [CV x\, \bar{r}]^2$$

$$\bar{r} \sim \mathrm{N}\ (\mathrm{a}_{1,}\ \mathrm{a}_2\ )$$

$$CV \sim U(\mathrm{b}_{1,}\, \mathrm{b}_2\ )$$

$$K \sim U(\max[catch],\ 35677)$$

$$q \sim U(0.0001,\ 3)$$

M2 and M3 differed from M1 in the type of error considered. M1 just took into account observation error uncertainty [$E(I_{i,t}) = q_i N_t e^{\varepsilon_i}$], and M2 and M3 also considered the process error uncertainty [$E(N_{t+1}) = N_t + G_t - C_t$]. M3 is different from M2, because *r* was modeled to be hierarchically structured and it simulated the possible variations of the population growth rates over time and space. The intrinsic rate of population growth, *r*, was assumed to follow a normal distribution with mean $\bar{r}$ and variance$[CVx\ \bar{r}]^2$, including mean $\bar{r}$ and coefficient of variation (CV) hyperparameters. $\bar{r}$ was assumed to follow a normal distribution with mean a_1 = 0.0661 and variance a_2 = 0.0996. These values are based on summarized information on the population growth rate of 80 shark species and stocks (Hoenig and Gruber 1990, Cailliet et al. 1992, Sminkey and Musick 1995, Smith et al. 1998, Cortes et al. 2002, Mollet and Cailliet 2002, Jiao et al. 2011). The carrying capacity, *K*, was assumed to follow a uniform distribution with lower bound equal to the maximum catch of scalloped hammerhead shark and upper bound 35677(*10^3), the estimated carrying capacity of large coastal shark (NMFS 2006).

When MCMC simulation was conducted to estimate parameters with uncertainty, the three methods tested (monitoring the trace for key parameters, diagnosing the autocorrelation plot for key parameters, and the Gelman and Rubin convergence diagnostic) failed to show evidence against convergence of the MCMC algorithm. The number of runs was equal to 10,000 (10,000 runs for each of the three chains/models) and before these runs, the burning period was discarded. The thinning interval was five.

Model Selection

To select a model over the other two that we used, we applied the Deviance Information Criterion (DIC):

$$DIC = 2\bar{D} - \hat{D} = \bar{D} + p_D$$

$D(y, \theta) = -2 \log likelihood(y | \theta)$

$p_D = \overline{D} - \widehat{D}$

where D is deviance, p_D is the effective number of parameters, $\overline{D}$ is the average deviance, and $\widehat{D}$ is the deviance evaluated at the posterior mean parameter estimates (Wilberg and Bence 2008). Here, y is I_i , and θ includes all the parameters in the corresponding models. The DIC is generally used when the posterior distribution of the models have been obtained with MCMC simulation (Spiegelhalter et al.2002, 2004).It is the Bayesian model comparison criterion, that quantifies the trade-off between the goodness of fit to the data and the complexity of the model (Spiegelhalter, 2006). DIC similar to other common used methods such as the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), penalize the complexity of the model. Models with smaller DIC values are more supported by the data.

We also calculated the probability that the estimated ratio of fishing mortality F relative to F_{MSY}, F/ F_{MSY} (fishery status), is greater than 1 [P(F> F_{MSY})], as an estimate of overfishing. The probability that the estimated population size relative to N_{MSY}, N/ N_{MSY} (population status), is smaller than 1 [P(N< N_{MSY}], were also estimated to evaluate the probability of the population being overfished. The estimates of these parameters were compared among different models and presented in a probabilistic way.

Results

Use of Bayesian state-space surplus production model (M2) resulted in smaller DIC values than using hierarchical model (M3) or surplus production model with measurement error only (M1). DIC values were very similar between M3 (76.851) and M2 (77.313), with M1 being the biggest of the three models tested (80.791; Table 3.4).

The posterior of *r* ranged from 0.37(M1) to 0.47 (M3), and the posterior of *K* varied from to 231.253(M2) to 145.68(M1), with the narrowest probability density function (pdf) of these parameters in M1 (Figure 3.4, Table 3.4).However, it may be just due to the fact that we didn't take uncertainty in the process equation for M1.

The indices for scalloped hammerhead sharks are of different length in the time series (Figure 3.2), so their influences on the model fitting are different. The models fit the indices to different degrees of goodness-of-fit (Figure 3.5). Because there are discrepancies among the indices, the overall trend tended to be more influenced by NCLL, which has a longer time series (Figure 3.5).

The population abundance estimates from the three models showed that population size has decreased since 1981; with the decreasing pattern being more stable since 1995 (Figure 3.6). There was an increase in abundance from 1986 to 1990 according to M1, but it could be due to the influence of the longest time series of the NCLL survey (Figure 3.5). The general pattern in the three models is the decline of the population from 1981 to 2005 (Figure 3.6). Use of the non-hierarchical model (M1, measurement error only) also resulted in abundance estimates with a narrower credible interval of key parameters than in the other two models (Figure 3.4). Population size in 1981 ranged from 101.3 $x10^3$ (M1) to 79.41 $x10^3$ (M3). N_{1981} was smaller when the hierarchical model was used than when the two non-hierarchical models were used (Figure 3.6).

When we looked to *Sphryrna lewini* population in 2005 regarding the virgin stock of the Atlantic and Gulf of Mexico coast of the USA, the depletion of the stock was 90.53% according to M1, 92.89% according to M2, and 91.69% according to M3(Table 3.4). Furthermore, overfishing occurred periodically from 1983 to 2005 (Figure 3.7). From this plot, we realized that the fishery is highly unstable, varying from one year to another according with three models tested. It could indicate that the population has a high variability in its recruitment, that added to the low grow rate of this species, contributing to even higher risk of overexploitation (Musick 2000).

A phase plot was prepared to compare the fishery and the population status among the three models tested in the last year of the assessment (2005; Figure 3.8). We found that fishing mortality was smaller than F_{MSY} [$F/F_{MSY}<1$)] in M1 and M3 (Table 3.4, Figure 3.8). The fishery was close to the limit of overfishing according to M1 and M3, but was above the limit according to M2 ($F/ F_{MSY} = 1.03$). The estimated population size relative to N_{MSY} (N/ N_{MSY} ; population status), was smaller than 1 . The population was overfished according to the three models tested, with M2 being the most conservative one (N_{2005}/N_{MSY} ~0.14; Table 3.4, Figure 3.8). M2 showed that the population size of scalloped hammerhead shark in 2005 was 14% of the population size at maximum sustainable yield (N_{MSY}).

Discussion

We found that state-space models with both process and observation error considered provided better estimates of the model parameters based on model goodness-of-fit (as He 2010). In our study, Bayesian state-space surplus production model, hierarchical and not-hierarchically structured, fitted the data better than the model with only observation error considered. The introduction of the process error into the model is important due to the simplicity of the process equation in the surplus production model and our ignorance of the whole ocean system. Bayesian methods permit the use of the observation-process error without making large assumptions (de Valpine and Hastings, 2002, Jiao et al. 2011). We didn't use just the process error because it was proved in past studies that this kind of error fit the data poorly (see Polacheck et al. 1993 as example).

Our study suggest that the status of the scalloped hammerhead shark on the western North Atlantic Ocean is more depleted than Baum et al. (2003) and Hayes et al. (2009) found (89% and 83% respectively), but less than Myers et al (2007) suggest (98%). Based on M2, which got the lowest DIC value, we estimated that the population had a 93% of decline in 2005 (Table 3.4). Furthermore, scalloped hammerhead shark population in the northwest Atlantic could be overestimated. There is a cryptic species, identical to *S.lewini*, that lives from South Carolina to Brazil and it only can be differentiated with genetic analysis (Pinhal et al. 2012). Catches of this cryptic species may have been included in the scalloped hammerhead catch data and therefore, overestimating the population (Miller et al. 2013). Ward-Paige et al. (2012) said that *Sphyrna lewini* stock in the western North Atlantic Ocean was one of the shark populations with evidence of recovery due to rebuilding management plans. However, the rate of increase that they showed it was very low, very close to zero, and moreover, they didn't take into account that possible caches of the cryptic species as scalloped hammerhead shark catches.

Jiao et al. (2011) used the hammerhead shark complex as an example to explore the advantages of using hierarchical Bayesian models in assessing the status of poor-data and data-poor exploited species when just process-measurement error is considered. They showed that hierarchical model borrowed strength from the species with relative good data of the hammerhead shark complex (scalloped) to the others with less quality of data (great and smooth), resulting in parameters estimates more stable and robust. They also checked the influence of difference prior values for *r, K* and *q,* getting smaller differences in the results when they used multilevel prior instead of simple priors. In our study with just the assessment of scalloped hammerhead sharks, we got better results for process-measurement error estimators than just measurement error estimator, but we couldn't choose hierarchical over non-hierarchical model due to the low difference between the DIC values.

Different relative abundance indices (Figures 3.2) may be of different quality as abilities to track the changes of the population abundance. Most of them don't cover the whole biological distribution area of *Sphyrna lewini*. For example, NMFS LL SE index has the greatest geographical distribution; therefore it could reflect population abundance better than smaller surveys. However, the NCLL abundance index has a big influence on the assessment due to the long time series and it could have problems due that has the same geographical coverage that the cryptic species. Future studies on the data uncertainty and quality would also help the overall stock assessment.

Prior selection can influence the parameters estimates and fishery status evaluation (Jiao et al. 2011). In this study we followed the well-recognized priors for *r,* so that we did not check the possible influence from different priors. Informative priors elicited from the previous studies often help the model parameter estimation especially when limited data/information available (such as this case; Gelman et al., 2004). However, other priors could be checked to ensure that our results were consistent. For example, future studies could compare the prior of *r* with the summary of the 80 species *versus* a summary with just the rate data of the sharks more similar to *S.lewini.*

The hierarchical model did not fit the scalloped hammerhead shark data better than the non-hierarchical Bayesian models. However, both models resulted in very similar DIC values. The limited differences in DIC values among the three models revealed the need for using various criteria to compare model performance and the possibility of using multi-model inference. Scalloped hammerhead shark data are not age-structured and we know that intraspecific population growth rates can change over time and space (Mangel et al. 2013). Increasing the uncertainty of this prior (using hierarchical models), confidence intervals of the parameters estimated can be wider (figure 3.4); however, these kinds of priors have been proven to be more robust than single-level priors (Andrews et al. 1993; Roberts and Rosenthal 2001; Clark 2003). A hierarchical Bayesian approach allows greater incorporation of variability in the model (Peterman et al. 2003, Beamish et al. 2009, Jiao et al. 2009b, 2011) and model results are often more robust than nonhierarchical models. However, for this specific species which is highly depleted and is cataloged as endangered by the IUCN, we recommend the process and measurement error to be both considered, and Bayesian hierarchical and non-hierarchical estimators to be used. Based on this study and that there was very low evidence of recovery according with last data available (Ward-Paige et al. 2012, Miller et al. 2013), we suggest prohibition of fishing for this species because: (1) it is highly depleted (14% of its initial population; an endangered species according to IUCN), (2) the fishery status is very unstable (3) it has a low reproductive rate contributing to a higher risk of overexploitation, and (4) the easiness of misidentifying different hammerhead sharks (smooth, great, scalloped and cryptic species).

References

Andrews, R. W., J. O. Berger, and M. H. Smith. 1993. Bayesian estimation of manufacturing effects in a fuel economy model. Journal of Applied Econometrics, Supplement: Special Issue on Econometric Inference Using Simulation Techniques, 8: 5–18.

Baum, J. K., D. G. Kehler, and R. A. Myers. 2005. Robust estimates of decline for pelagic shark populations in the northwest Atlantic and Gulf of Mexico. Science 299, 389-392.

Baum, J. K., R. A. Myers, D. G. Kehler, B. Worm, and S. J. Harley. 2003. Collapse and conservation of shark populations in the northwest Atlantic. Science 299, 389-392.

Beerkircher, L. R., C. J. Brown, and D. W. Lee. 2002. SEFSC pelagic observer program data summary for 1992-2000.NOAA Technical Memorandum NMFS-SEFSC-486. NOAA, Miami, Florida, USA.

Cailliet, G. M., H. F. Mollet, G. G. Pittenger, D. Bedford, and L. J. Natanson. 1992. Growth and demography of the Pacific angel shark (*Squatina californica*), based upon tag returns off California. Australian Journal of Marine and Freshwater Research 43:1313–1330.

Carlson, J. K., I. E. Baremore, and D. M. Bethea. 2005. The directed shark gillnet fishery catch and bycatch, 2004. Sustainable Fisheries Division Contribution PCB-05-01.Sustainable Fisheries Division, Panama, City, Florida, USA.

Carlson, J. K., and D. M. Bethea. 2005. Standardized catch rates of large coastal sharks from a fishery-independent survey in northeast Florida. Southeast Data, Assessment and Review (SEDAR) 11, Large Coastal Shark Data Workshop LCS05/06-DW-12. Sustainable Fisheries Division, Panama City, Florida, USA.

Chapman, D. D., D. Pinhal, and M. S. Shivji. 2009. Tracking the fin trade: genetic stock identification in western Atlantic scalloped hammerhead sharks *Sphyrna lewini*. Endangered Species Research 9: 221-228.

Clark, J. S. 2003. Uncertainty and variability in demography and population growth: a hierarchical approach. Ecology 84:1370–1381.

Cortes, E. 2002. Incorporating uncertainty into demographic modeling: application to shark populations and their conservation. Conservation Biology 16:1048–1062.

Cortés, E., A. Morgan, and G. Burgess. 2005. Standardized catch rates of large coastal sharks from the commercial shark fishery observer program, 1994-2004. Southeast Data, Assessment and Review (SEDAR) 11, Large Coastal Shark Data Workshop LCS05/06-DW-17. Sustainable Fisheries Division, Panama City, Florida, USA.

De Valpine, P., and A. Hastings. 2002. Fitting population models incorporating process noise and observation error. Ecological Monographs **72**:57–76.

Gelman, A., and D. B. Rubin. 1992. Inference from iterative simulation using multiple sequences (with discussion). Statistical Science 7:457–511.

Gelman, A., J. B. Carlin, H. S. Stern, and D.B. Rubin. 2004. Bayesian data analysis. Chapman and Hall, London, UK.

Hayes, C. 2008. Investigating single and multiple species fisheries management: stock status evaluation of hammerhead (Sphyrna spp.) sharks in the western North Atlantic and Gulf of Mexico. Thesis. Virginia Tech University, Blacksburg, Virginia, USA.

Hayes C., Y. Jiao, and E. Cortés. 2009. Stock assessment of scalloped hammerheads in the Western North Atlantic Ocean and Gulf of Mexico. North American Journal of Fisheries Management 29: 1406–1417.

He, Q. 2010. Investigating the performance of process observation-error-estimator and robust estimators in surplus production model: a simulation study. Thesis. Virginia Tech University, Blacksburg, Virginia, USA.

Hilborn, R., and C. Walters. 1992. Quantitative fisheries stock assessment: choice, dynamics, and uncertainty. Chapman and Hall, New York, New York, USA.

Hilborn, R. and M. Mangel. 1997. The ecological detective: confronting models with data. Princeton University Press.

Hoenig, J. M., and S. H. Gruber. 1990. Life history patterns in the elasmobranchs: implications for fisheries management. Pages 1–16 in H. L. Pratt, Jr., S. H. Gruber, and T. Taniuchi, editors. Elasmobranchs as living resources: advances in the biology, ecology, systematics, and the status of the fisheries. NOAA Technical Report NMFS 90. NOAA, Silver Spring, Maryland, USA.

Ingram, W., T. Henwood, M. Grace, L. Jones, W. Driggers, and K. Mitchell. 2005. Catch rates, distribution, and size composition of large coastal sharks collected during NOAA. Fisheries bottom longline surveys from the U.S. Gulf of Mexico and U. S. Atlantic Ocean. Southeast Data, Assessment and Review (SEDAR) 11, Large Coastal Shark Data Workshop LCS05/06-DW-27. Sustainable Fisheries Division, Panama City, Florida, USA.

IUCN 2013. IUCN Red List of Threatened Species. Available : www.iucnredlist.org. (September 2013).

Jiao, Y., R. Neves, and J. Jones. 2008. Models and model selection uncertainty in estimating growth rates of endangered freshwater mussel populations. Canadian Journal of Fisheries and Aquatic Sciences 65:2389–2398

Jiao, Y**.,** K. Reid, T. Nudds, and E. Smith. 2009a. Graphical evaluation of fishery status with a likelihood inference approach. North American Journal of Fisheries Management. 29:1106-1118.

Jiao, Y., C. Hayes, and E. Cortés. 2009b. Hierarchical Bayesian approach for population dynamics modelling of fish complexes without species-specific data. ICES Journal of Marine Science, 66: 367–377.

Jiao, Y., E.Cortés, K. Andrews, F. Guo. 2011. Poor-data and data-poor species stock assessment using a Bayesian hierarchical approach. Ecological Application 21: 2691–2708.

Mangel, A., A. MacCall, J. Brodziac, E. Dick, R. Forrest, R. Pourzand, and S. Ralston. 2013. A perspective on steepness, reference points, and stock assessment. Canadian Journal of Fisheries and Aquatic Sciences 70(6): 930-940.

May, R. M., J. R. Beddington, C. W. Clark, S. J. Holt, and R. M. Laws. 1979. Management of multispecies fisheries. Science 205: 267–277.

McCandless, C. T., and C. N. Belcher. 2007. Standardized catch rates of small coastal sharks from the Georgia COASTSPAN and GADNR penaeid shrimp and blue crab assessment surveys. National Marine Fisheries Service, Southeast Fisheries Science Center, SEDAR 13-DW-27, Narragansett, Rhode Island.

Miller, M. H., J. Carlson, P. Cooper, D. Kobayashi, M. Nammack, and J. Wilson. 2013. Status review report: scalloped hammerhead shark (*Sphyrna lewini*). Report to National Marine Fisheries Service, Office of Protected Resources. March 2013.131 pp.

Mollet, H. F., and G. M. Cailliet. 2002. Comparative population demography of elasmobranchs using life history tables, Leslie matrices and stage-based matrix models. Marine and Freshwater Research 53:503–516.

Myers, R. A., J. K. Baum, T. D. Shepherd, S. P. Powers, and C. H. Peterson. 2007. Cascading effects of the loss of apex predatory sharks from a coastal ocean. Science 315: 1846-1850.

Natanson, L. 2007. National Marine Fisheries Service, Southeast Fisheries Science Center, SEDAR 11 LCS05/06-DW-33, Narragansett, Rhode Island.

NMFS, 2006. SEDAR 11. Stock assessment report: large coastal shark complex, blacktip and sandbar shark. US Dept. Commerce, NOAA, NMFS, Highly Migratory Species, Silver Spring, MD, 387 pp.

Pinhal, D., M. S Shivji, M. Vallinoto, D. D. Chapman, O. B. F. Gadig, and C. Martins. 2012. Cryptic hammerhead shark lineage occurrence in the western South Atlantic revealed by DNA analysis. Marine Biology 159: 829-836.

Polacheck, T., R. Hilborn, and A. E. Punt. 1993. Fitting surplus production models: comparing methods and measuring uncertainty. Canadian Journal of Fisheries and Aquatic Science 50: 2597-2607.

Punt, A. E. 1992. Management procedures for Cape hake and baleen whale resources. Benguela Ecology Programme Report 23, 689 pp.

Punt, A. E., and R. Hilborn. 1997. Fisheries stock assessment and decision analysis: the Bayesian approach. Review in Fish Biology and Fisheries.7: 35–63.

Roberts, G. O., and J. S. Rosenthal. 2001. Infinite hierarchies and prior distributions. Bernoulli 7:453–471.

Schwartz, F. J., C. T. McCandless, and J. J. Hoey. 2007. Trends in relative abundance for shark species caught during a UNC longline survey conducted between 1972 and 2005 in Onslow Bay, NC. SEDAR 13-DW-34-V2. Sustainable Fisheries Division, Panama City, Florida, USA.

Sminkey, T. R., and J. A. Musick. 1995. Age and growth of the sandbar shark, Carcharhinus plumbeus, before and after population depletion. Copeia 1995:871–883.

Smith, S. E., D. W. Au, and C. Show. 1998. Intrinsic rebound potentials of 26 species of Pacific sharks. Marine and Freshwater Research 49:663–678.

Spiegelhalter, D. J., N. G. Best, B. P. Carlin, and A. van der Linde. 2002. Bayesian measures of model complexity and fit (with discussion). Journal of the Royal Statistical Society Series B 64:583–640.

Spiegelhalter, D. J., A. Thomas, N. Bestand, and D. Lunn. 2004. WinBUGS user manual (version 1.4.1). MRC Biostatistics Unit, Cambridge, UK.

Spiegelhalter, D. (2006), 'Some dic slides', MRC Biostatistics Unit, Cambridge.

Ward-Paige, C. A., D. M. Keith, B. Worm, and H. K. Lotze. 2012. Recovery potential and conservation options for elasmobranchs. Journal of Fish Biology 80: 1844-1869.

Wilberg, M. J., and J. R. Bence. 2008. Performance of deviance information criterion model selection in statistical catch-at-age analysis. Fisheries Research 93: 212-221.

Tables

Table 3.1: National Marine Fisheries Services shark management unit (NMFS, 2006).

Management Unit	Sharks Species Included
Large Coastal Sharks (11)	sandbar, silky, tiger, blacktip, bull, spinner, lemon, nurse, smooth hammerhead, scalloped hammerhead, great hammerhead
Pelagic Sharks (5)	shortfin mako, thresher, oceanic whitetip, porbeagle, blue
Small Coastal Sharks (4)	Atlantic sharpnose, blacknose, finetooth, bonnethead
Prohibited species (19)	whale, basking, sand tiger, bigeye sand tiger, white, dusky, night, bignose, Galapagos, Caribbean reef, narrowtooth, longfin mako, bigeye thresher, sevengill, sixgill, bieye sixgill, Caribbean sharpnose, smalltail, and Atlantic angel sharks

Table 3.2: Catches (in numbers of individuals) of *Sphyrna lewini* since 1981 to 2005. Blanks indicate missing data (NMFS 2006).

Year	Recreational	Commercial	Discards	Total
1981	5880	0		5880
1982	48138	1		48139
1983	20962	365		21327
1984	7003	0		7003
1985	44042	0		44042
1986	5321	0		5321
1987	6372	0	1228	7600
1988	4518	2	1674	6194
1989	6191	0	1389	7580
1990	18373	12	1151	19536
1991	8935	4	1221	10160
1992	7325	67	2257	9649
1993	21723	91	516	22330
1994	3886	301	368	4555
1995	3695	1479	567	5741
1996	882	1479	290	2651
1997	3905	1041	938	5884
1998	1083	642	234	1959
1999	545	386	344	1275
2000	6350	68	277	6695
2001	1112	1152	339	2603
2002	6113	1180		7293
2003	2859	2606		5465
2004	803	1351		2154
2005	803	2901		3704

Table 3.3: Summary of relative abundances indices for scalloped hammerhead sharks.

Index	Geographic coverage	Fishery Dependence	Units	Years	Reference
NMFS LL SE	South Atlantic and Gulf of Mexico	FI	Sharks per 10000 hook hours	1995-2005	Ingram et al.(2005)
PCGN	Northeastern Gulf of Mexico	FI	Gillnet: Sharks per net per hour	1996-2005	Carlson and Bethea (2005)
NCLL	Onslow Bay, North Carolina	FI	Shark per hook	1972-2005	Schwartz et al. (2007)
CSFOP	South Atlantic and Gulf of Mexico	FD	Sharks per 100 hooks per hour	1994-2005	Cortes et al. (2005)
GNOP	South Atlantic (Georgia, Florida) and Gulf of Mexico (Florida)	FD	Drift gillnet: Sharks per 107 m2 per hour	1994-2005	Carlson et al. (2005)
PLLOP	Western North Atlantic	FD	Sharks per 1000 hooks	1992-2005	Beerkircher et al. (2002)
GACP	Georgia estuaries	FI	Trawl	2000-2005	McCandless & Belcher (2007)
NMFS LL NE	South Atlantic (Florida to Delaware)	FI	Longline	1996-2005	Natanson(2007)

Table 3.4: Key parameters values from the logistic surplus-production model under the three Bayesian models.

Parameters	BAYESIAN+ Measurement (M1)	BAYESIAN+ Process and Measurement (M2)	Hierarchical (M3)
r	0.37	0.39	0.47
$K(*10^3)$	145.68	231.25	203.97
$N_{1981}(*10^3)$	101.30	94.06	79.41
Depletion (N_{2005}/K)	0.09	0.07	0.08
N_{2005}	13.80	16.44	16.95
N_{MSY} (k/2)	72.84	115.63	101.98
MSY(r*K/4)	12.87	20.51	21.55
F_{MSY} (r/2)	0.19	0.19	0.24
F_{2005}(Catch/N)	0.16	0.20	0.18
F_{2005}/F_{MSY}	0.83	1.03	0.74
N_{2005}/N_{MSY}	0.19	0.14	0.17
DIC values	80.791	76.851	77.313

Figures

Figure 3.1: Catches of Scalloped hammerhead shark (S. *lewini*) from 1981 to 2005 on the western North Atlantic Ocean.

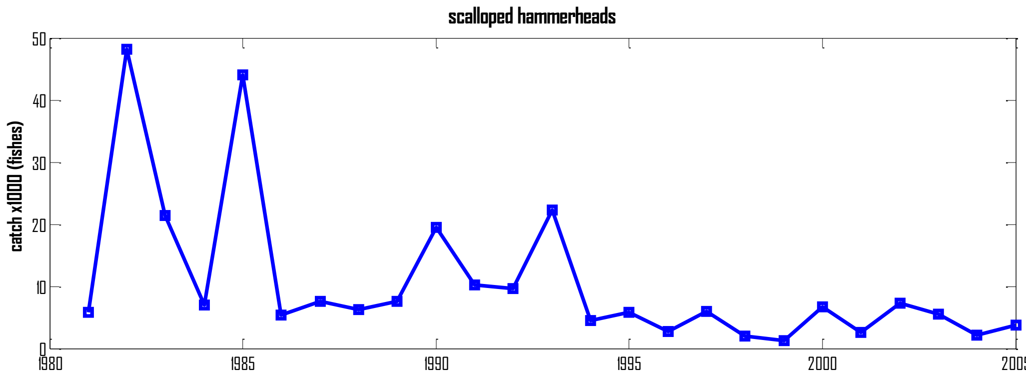


Figure 3.2: Indices of relative abundance of scalloped hammerhead sharks recommended by SEDAR: the NMFS Mississippi bottom longline shark survey (NMFS-LL-SE; Ingram et al. 2005), the NMFS Panama City gillnet shark survey (PCGN,; Carlson and Bethea 2005), the University of North Carolina longline survey (NCLL; Schwartz et al. 2007), the commercial shark fishery observer program (CSFOP; Cortés et al. 2005), the shark drift gillnet observer program (GNOP; Carlson et al. 2005), and the pelagic longline observer program (PLLOP; Beerkircher et al. 2002).

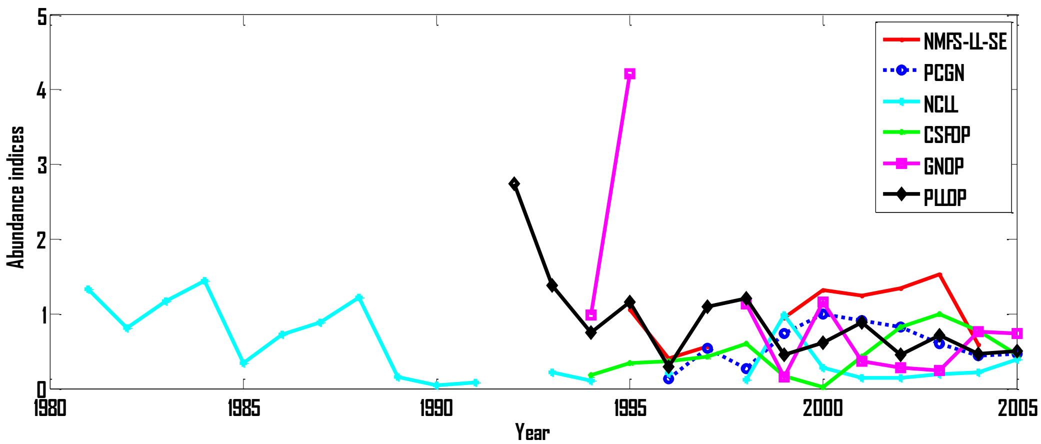


Figure 3.3: Catch composition of scalloped hammerhead shark fishery data.

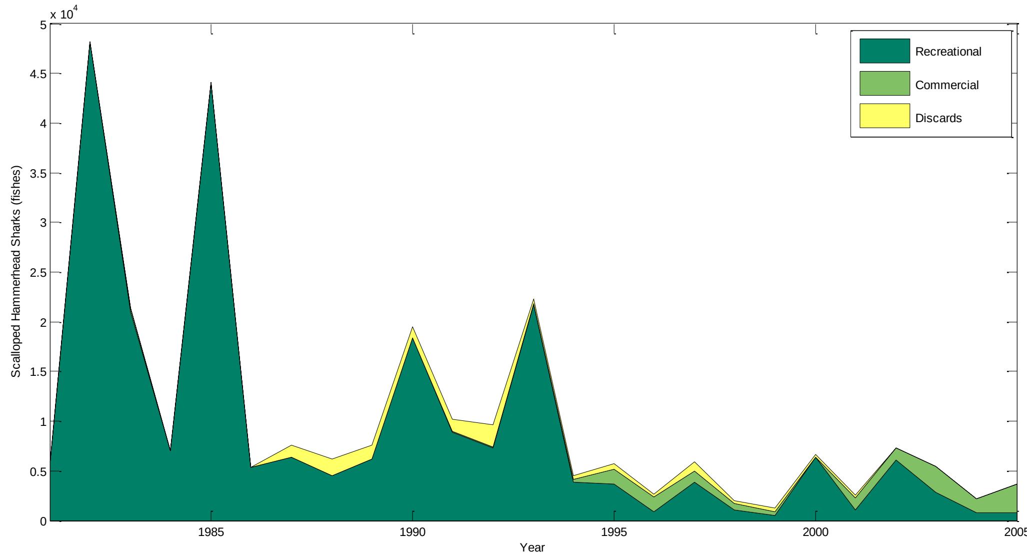


Figure 3.4: Probability density functions (pdf's) of growth rate(r), carrying capacity (*K*), current population size (N_{cur}), and depletion for the three models ($SSHg_M$ = M1or measurement error only model; SSHg = M2 or measurement-process error model, HierH= M3 or Hierarchical model).

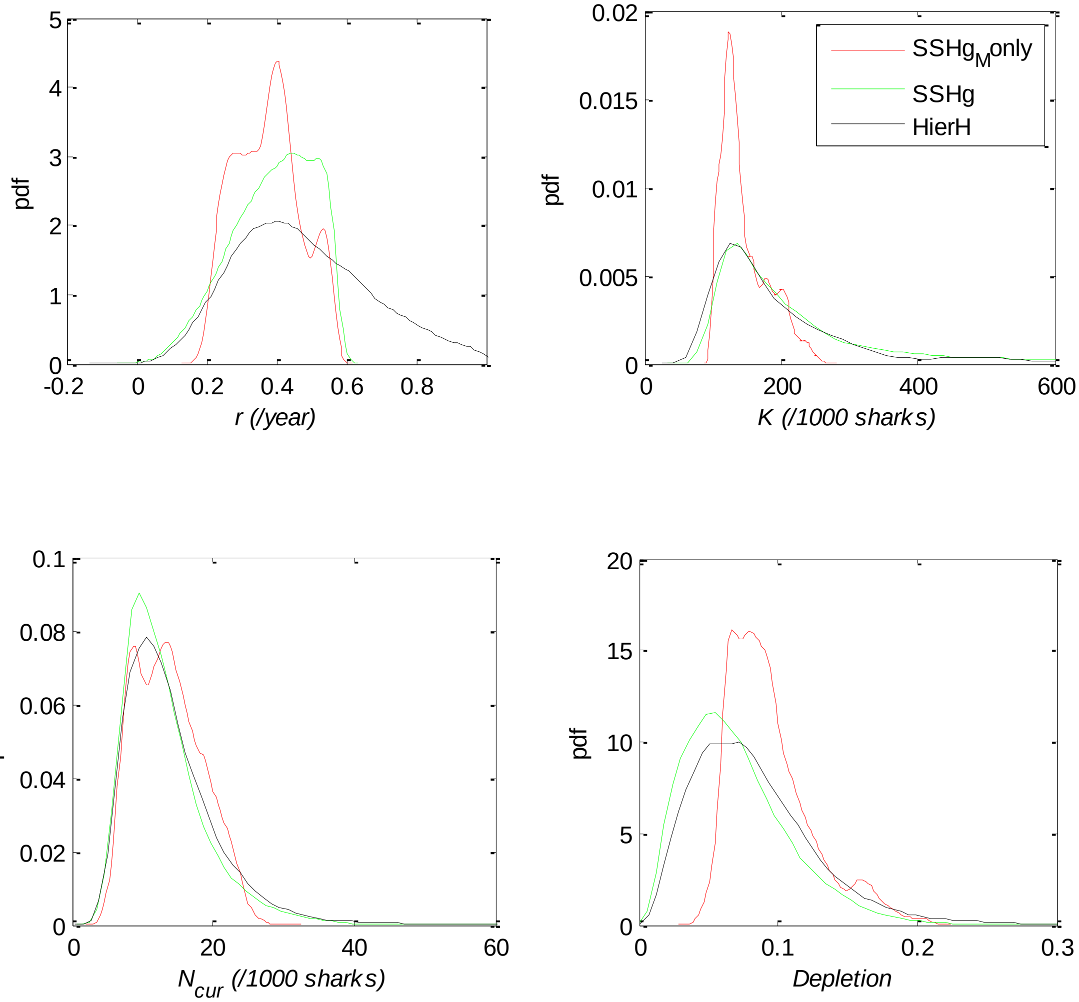


Figure 3.5: Model fit to the logarithm of relative abundances indices from the three models ($SSHg_M$ = M1or measurement error only model; SSHg = M2 or measurement-process error model, HierH= M3 or Hierarchical model).

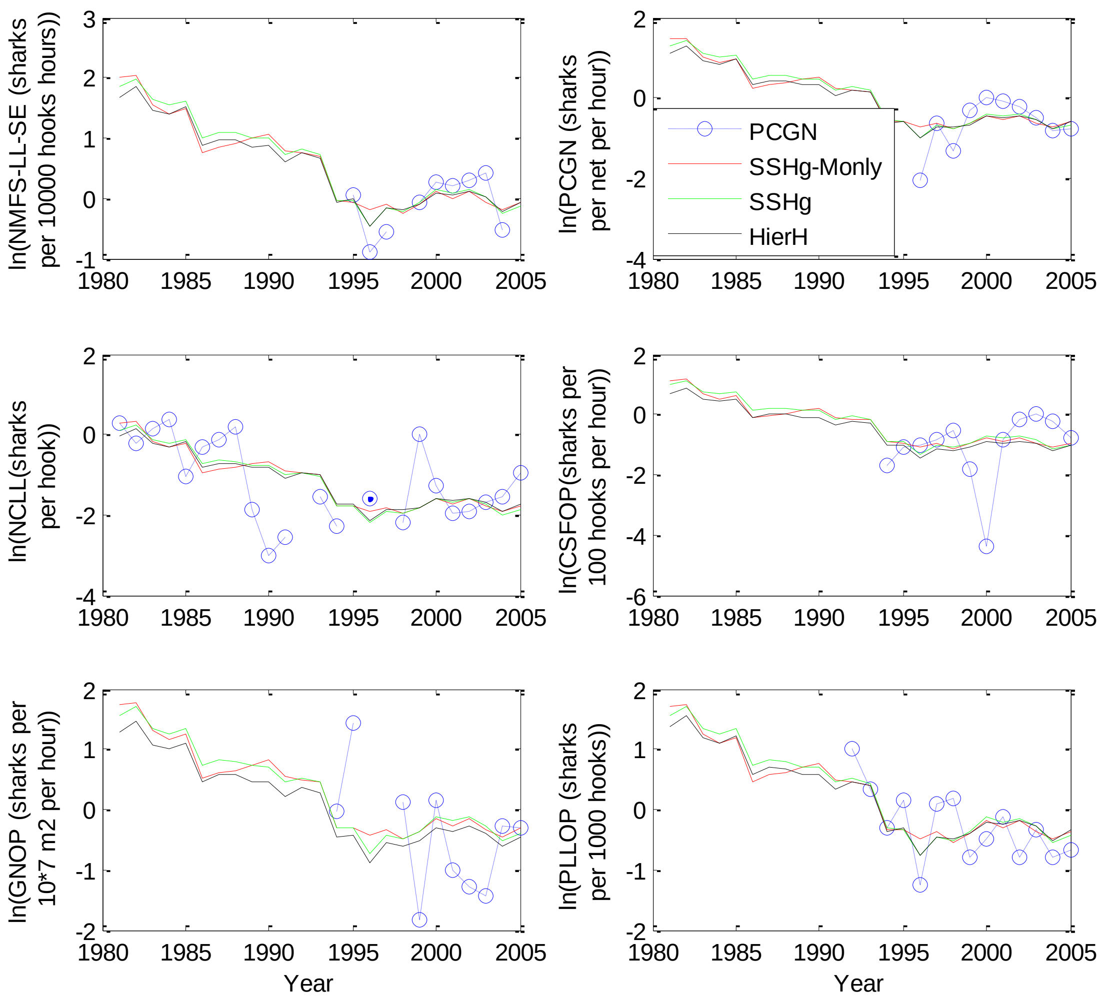


Figure 3.6: Population abundance trajectories for scalloped hammerhead shark. Solid lines denote the posterior mean of population abundance; dotted lines denote 95% credible intervals of population abundance. M1 (red lines), M2 (green lines) and M3 (black lines).

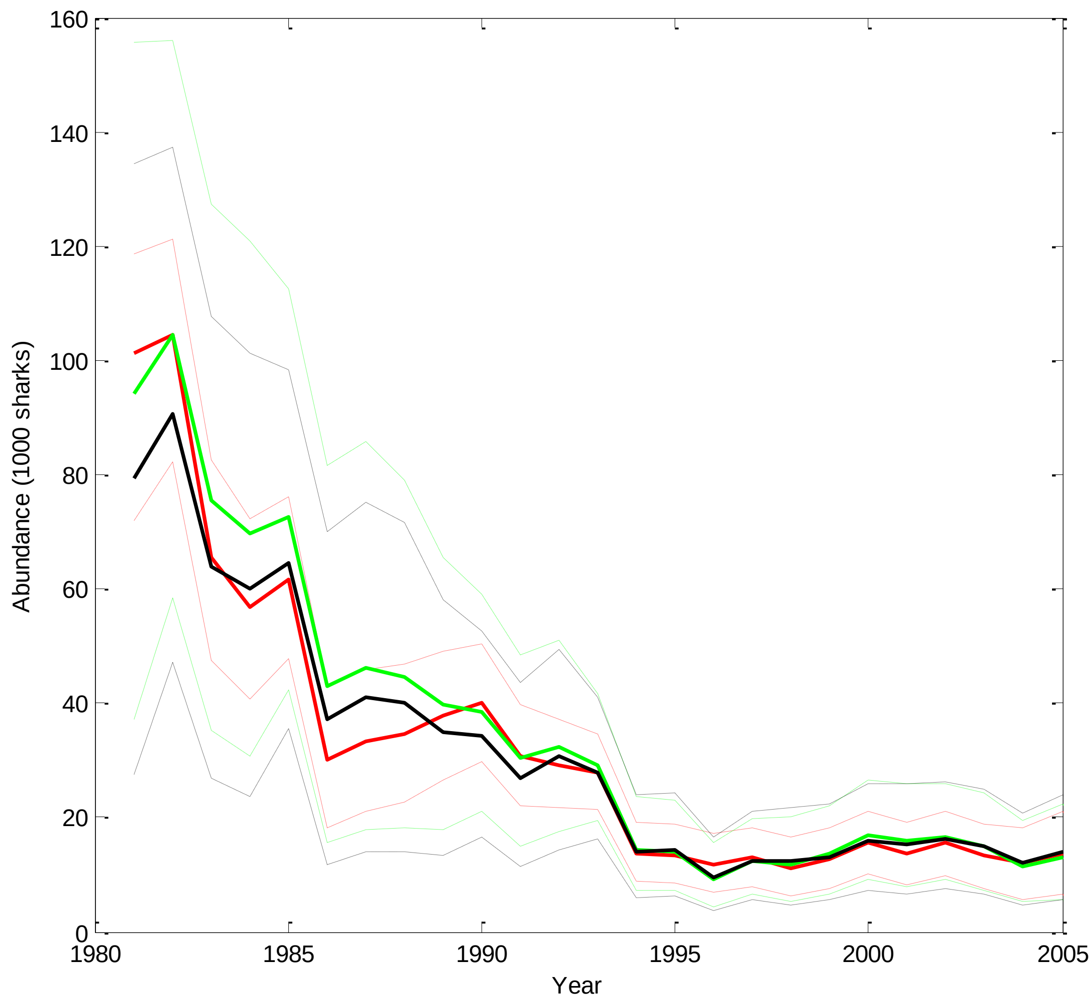


Figure 3.7: Estimated fishing mortality rate of scalloped hammerhead sharks for 1981-2005.Solid lines denote the posterior mean of population abundance; dotted lines denote 95% credible intervals of fishing mortality. M1 (red lines), M2 (green lines) and M3 (black lines).

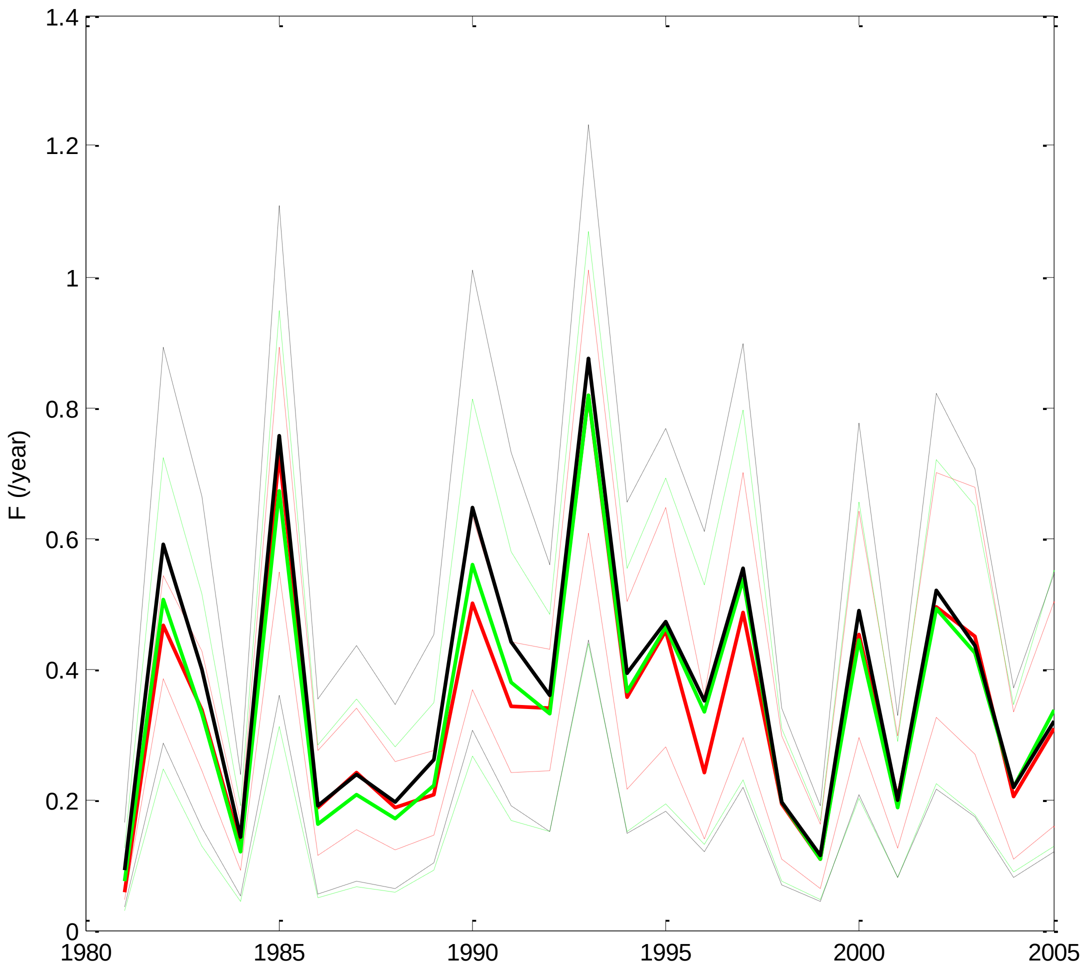


Figure 3.8: Phase plot for scalloped hammerhead sharks showed the population size in 2005 relative to N_{MSY} and fishing mortality in 2005 relative to F_{MSY} when the M1(measurement error only model) , M2(measurement-process error model), and M3(hierarchical model) were applied (NOTE: the safe quarter = bottom-right quarter).