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COMPARISON OF TWO STOCK ASSESSMENT MODELS OF NAMIBIAN MONKFISH (LOPHIIFORMES*)*.

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ABSTRACT

Fisheries management relies on stock assessment models to provide estimates of population abundance and to shed light on the underlying dynamics of the resources being managed. It is necessary to quantify and understand the uncertainty about model parameters and reference points to evaluate the consequences of alternative management actions. This report presents a comparison of two different assessment methods and the state of the Namibian monkfish stock (*Lophius vomerinus* and *L. vaillanti*) in Namibian waters. The objective of this study is to compare the currently used ASPM model implemented in Automatic Differentiation Model Builder (ADMB) on monkfish assessment with an a4a model to see if they return similar management advice. Two age-based alternative assessment methods are used: Age Structure Production Model (ASPM) and the Assessment for All Initiative (a4a) model implemented in the R package (The Fisheries Library in RFLR). Most of the data used in this study are from the National Marine Research Information Centre (NatMRIC). Age-disaggregated observations are used as input data and a Beverton-Holt (B-H) stock-recruitment relationship was used to estimate recruitment for both models. Recruitment was high for 2017 and it is around 15 billion and 30 billion according to the ASPM and a4a models, respectively, but the ASPM model estimated the spawning stock biomass as higher than the a4a models. The different models gave similar trends but were dissimilar in fishing mortality rates over the period studied (2000-2016). The fishing mortality estimated by the two models is between 0,2 to 0,35 with the highest estimate given by the a4a model in 2016. Short-term predictions from the a4a model suggested that recruitment and spawning stock biomass will decrease by 30 % over the next three years (2017-2019) while the fishing mortality is predicted to be higher than the current level (2016), if fishing effort remains the same.

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1 INTRODUCTION

The fishery sector is one of the primary contributors to Namibia's economy. The sector employed about 25,000 people in 2012 (Chiripanhura & Teweldemedhin, 2016). Most of the employment opportunities come directly from the marine commercial fisheries. Fishing and fish processing on board contributes about 2.9 % to the country's (Gross Domestic Production) GDP (NSA, 2015). Key species are regulated through Total Allowable Catches (TAC) and a quota allocation system. The demersal species that are managed through TACs are: hake (*Merluccius capensis* and *M. paradoxus*), monkfish (*Lophius vomerinus* and *L. vaillanti*) which belong to the Lophiidae family, deep sea red crab (*Chaceon maritae*), rock lobster (*Jasus lalandii*) and orange roughy (*Hoplostethus cadenati*). Other TAC-regulated species are pelagic, including Cape horse mackerel (*Trachurus capensis*), pilchard (*Sardinops sagax*) and the Cape fur seal (*Arctocephalus pusillus*). TACs are recommended based on stock assessment models that require annual surveys and catch per unit effort (CPUE) indices obtained from the fishery.

While the monkfish resource became increasingly economically important as catches and demand have increased, it has become imperative to accumulate and analyse information on the biology, abundance and fisheries of the species. Numerous aspects such as the dynamics of the fleet, the effort distribution, spatial variability, temporal variability and the variability in the annual catch rates were explored (Brandão, 2006). Namibian monkfish research commenced in 1993 and between 1994 and 1996, stock assessment concentrated on length-based models to assess the status of the resource and to estimate relative biomass indices from the hake-directed research survey (Maartens et al, 2001). Since 2000, the Ministry of Fisheries and Marine Resources has conducted annual biomass surveys on the monkfish in Namibia. Surveys conducted between 2000 and 2015 showed the monkfish to be distributed between 17°S and 30°S occurring mainly between depths of 130-800 m. *L. vaillanti* is distributed northward from around 23°S while *L. vomerinus* is distributed along the entire coastline. *L. vomerinus* makes up to 99% of the total monkfish landings (iiyambo, 2006) and can reach an asymptotic length of 110 cm (Nangolo, 2016) and may live in excess of 10 years. The largest monkfish measured on an annual monkfish biomass survey from 2000-2015 was 102 cm, and the oldest was 14 years.

CPUE data must be standardised before they can be incorporated in stock assessment models, because they are intended to relate information about the relative abundance of the stock but can also vary with other conditions, for example seasons or changes in stock distribution (Deriso,et al., 1985). Therefore, the ability to use catch rate data as an index of abundance depends on being able to adjust for (changes in catch rates over time which depend on factors other than abundance, e.g. technological advances in fishing (Maunder & Punt, 2004). One commonly used CPUE standardisation method involves using a generalised linear model (GLM). CPUE analyses using multiplicative models have become widely used in assessing fish stocks (Gavaris, 2011). GLM is used to compute a CPUE index as input into the current age-structured production model (ASPM). Previous studies have addressed the problem of interpreting monkfish catch statistics in the light of changes occurring under the Namibian individual vessel quota (IVQ) program. CPUE in particular was examined to determine if vessel size and the behaviour of the fleet over time and at different locations influences annual variations in those statistics (Maartens et al, 1999) (Maartens , 2001). This study explores other standardisation options but uses the original standardisation for model comparison purposes.

Stock assessment can be defined as the application of quantitative and statistical models to estimate the current and historical status and trends of a fish stock, including abundance, mortality, and productivity (Hilborn and Walters, 1992). Model comparison plays a central role in statistical evaluation of modelling fisheries. Models are compared by looking at which model minimise the error in the estimation process. It is statistically advisable to consider a simple, understandable and above all, useful model for decision making in fisheries management. When possible, performance of models is evaluated using a given criterion based on which models can be compared. There exist a variety of criteria that can be applied for model assessment, such as Akaike’s information criterion (AIC), Bayesian information criterion (BIC), deviance information criterion (DIC), and many more. There is a large body of literature that is devoted to these criteria. For example, a model with a smaller AIC or BIC is preferred if AIC or BIC are chosen for model analysis. However, models cannot be compared when different data are used to fit them. In this case, models must be qualitatively compared using diagnostic plots that show the fit of the model to the data and experimental manipulation of model settings to understand how different model components affect management advice.

The goal of this study is to compare the currently used ASPM model on monkfish assessment with the a4a model. The ASPM model was built in ADMB framework, but the model implementation is complex, which makes it inflexible and hard to comprehend. In contrast, the a4a model was developed in the Fisheries Library in R FLR framework (Ernesto et al, 2014) to simplify the analysis of stock assessment, and also to increase the accessibility of running stock assessments on other species, while simultaneously promoting the inclusion of the major sources of uncertainty in scientific advice (Ernesto, 2014). It is more easily implemented but has a different model structure than the ASPM model and utilises a shorter time series of data. This study compares diagnostic plots and management advice resulting from each model. In addition, standardisation methods using GLM will be explored and selected using AIC model selection criteria.

1.1 Rationale and Objectives

There has been a need to compare ASPM to other aged based models or stock assessment models that can use minimal age structured data and review the model used on monkfish in order to reduce uncertainty and prevent bias in the stock assessment. The model is complex and there is a lack of understanding on how the model was designed, and therefore has not been updated or validated recently. It is possible that the assumptions in the model are no longer valid, but evaluation and modification of the model cannot readily be done due to the complexity of the model. For example, the main gear used in the fishery has changed from a single belly to a double belly trawl, which may affect catchability. Hence, there is a need to identify a similar model which can improve knowledge on monkfish model assessment and help scientists to interpret the outcomes in order to provide advice on setting the TAC.

The general objective of the research is to reduce uncertainty and/or bias in the assessment of monkfish by comparing ASPM and a4a model results. More specifically the project aims at:

- Standardising CPUE indices.
- Implementing a new monkfish stock assessment model using R statistical framework.

- Comparing model input data, data processing, model output/fits, and indicators of the stock status from the two models.

2 LITERATURE REVIEW

2.1 Biology of monkfish

Lophiidae is a well-known family of sit-and-wait predators with a characteristic flattened shape and camouflaged skin adapted to the sandy and muddy bottom of the continental slope. They are opportunistic gape-limited foragers, in that they eat whatever comes into reach and fits into their mouths. They lure their prey by moving angling-like organs, referred to as illicium, which is the first spine on their dorsal fin modified with a light producing organ on the end (Froese, 2017).

The family includes seven species distributed around the world. The white anglerfish (*Lophius piscatorius)* is found in the northeast Atlantic Ocean and the Mediterranean Sea, and the black anglerfish (*Lophius budegassa*) coexists with white anglerfish over most of its range, although the black anglerfish has a more southerly distribution in the Atlantic (Caruso, 1986). The shortspine African angler (*Lophius vaillanti*) is found in the eastern Atlantic (Maartens and Booth, 2005). The devil anglerfish (*Lophius vomerinus*) occupies the southeast Atlantic and the northern and western Indian Ocean (Walmsley, 2005). The blackfin goosefish (*Lophius gastrophysus*) inhabits the western Atlantic, and the goosefish (*Lophius americanus*) occurs in the northwest Atlantic (Caruso, 1986). Finally, the yellow goosefish (*Lophius litulon*) is distributed in the northwest Pacific, in the Gulf of Po-Hai, in the Yellow Sea, and in the East China Sea. The genus supports valuable fisheries (except for *Lophius vaillanti*) (Caruso, 1986).

Data on gonads indicate repeat spawning, so that *L. vomerinus* spawn throughout the year with a slight increase in spawning intensity from the winter period through to early fall depending on latitude. *L. vomerinus* spawn a flat gelatinous egg mass, called veils, into the water, which float near the surface. Larvae and juveniles are pelagic and remain in this stage for several months before they settle to the bottom at a size of about 7.6 cm. Female monkfish mature at both a larger size and at a greater age than the male of the same age. Males have not been found older than age nine, and their total lengths reach approximately 88.9 cm. Out of the seven-species included in the *Lophius* genera, two (*L. vomerinus* and *L. vaillanti*) are found and fished commercially in Namibian waters (Caruso J. H., 1986).

L. vomerinus is commonly found in waters deeper than 100 m, with the main part of the stock being distributed between 100 m and 500 m water depth. Historical data available on the reproductive biology of *L. vomerinus* in Namibia are restricted to the geographical positions of recruitment areas, i.e. areas with high abundance of 0-group aged fish. Member countries of the International Commission for South-East Atlantic Fisheries ICSEAF, and in particular Spanish researchers, identified two separate areas, the first being off Walvis Bay (23° - 25°S) at depths between 150 and 300 m, and the second near the Orange River (28°35’S) at depths between 100 and 300 m. These observations confirm independent data collected by the Norwegian *RV Dr. Fridtjof Nansen* during bottom trawl surveys in the (MFMR, 2017). The other species of *Lophiiformes* group, *L. vaillanti* is less abundant but with same market value as *L. vomerinus*. L.*vaillanti* is commonly found in the northern parts of Namibian waters deeper than 400 m (Caruso J. H., 1986).

2.2 Monkfish fishery

The marine ecosystem of Namibia, which forms part of the South Atlantic Ocean, is characterised by the nutrient-rich upwelling Benguela current. This coastal upwelling in the Benguela region is important because of its high productivity (Sumaila, et al., 2004). Commercially important species such as hake, monkfish and many more depend on this productive ecosystem. Monkfish catches are controlled by a quota management system in addition to limited entry licensing in the monkfish-fleet and sole directed fleet, and by bycatch levies in the hake-directed fleet.

There are about 19 vessels that target monkfish which were active in the fishing grounds in 2016. The monkfish sub-sector employed about 318 fishermen. Monkfish is mainly exported to Spain and Italy (MFMR, 2016). The Namibian competitive advantage lies in long-term marketing agreements they have with European distributors. Namibia faces competition since countries such as Canada, China, Chile, India, Indonesia, Netherlands, Norway, Sweden, Vietnam and USA also export monkfish products (Amupolo, 2006).

2.3 Monkfish survey

Since 2000, the Ministry of Fisheries and Marine Resources has conducted annual biomass surveys for the monkfish in Namibia in November. During the survey new staff and university students are trained on sample collection. Samples for ageing, biological data of monkfish and environment factors are collected for different studies during monkfish surveys. Currently the survey is conducted by the research vessel RV Mirabilis (2014 to 2016) which took over from the old research vessel RV Welwitchia (2000 to 2013). In order to keep consistency in data collection and comparability of data time series in fisheries research, gear and sampling methods should be standardised (T.Endjambi, 2017). However, the calibration factor between the two vessels is still to be agreed upon.

2.4 Background on the ASPM for Namibian monkfish

An Age Structure Production Model (ASPM), which assessment was developed in 2001 using the ADMB software, is currently used to assess the monkfish stock. Since 2001 the monkfish has been assessed annually. Indices of abundance are derived from two independent monitoring programs: annual scientific swept-area biomass survey estimates, and standardised commercial CPUE index. It must be noted that commercial trawl gear modification has happened over the years in the monkfish fishery. Model parameters (stock-recruitment function parameters together with annual deviations from this relationship, selectivity and multiplicative error parameters, and yearly fishing mortalities) are estimated by penalised maximum likelihood in the model. For the ASPM, the negative log-likelihood function is minimised with respect to the unexploited equilibrium spawner-biomass (K^{sp}). The K^{sp} for the values of q ranging from 0.5 to 1.1, resulting in 11 different model results. In addition, steepness and annual recruitment are estimated within the model by using the information inherent in the catch-at-age matrix (MFMR, TAC report 2016).

Monkfish catches have fluctuated over time, but the spawning stock biomass estimates from the current ASPM assessment have been decreasing from about 10,000 t in 1974 to 40% of that in 2016 (Figure 1). The drop in 1990 is related to transformation of fishing system which was due to Namibian independence and not necessarily some drop-in catches. Since independence, catches have been around 7000 t for the years 1998-2003 with a peak around 2000.

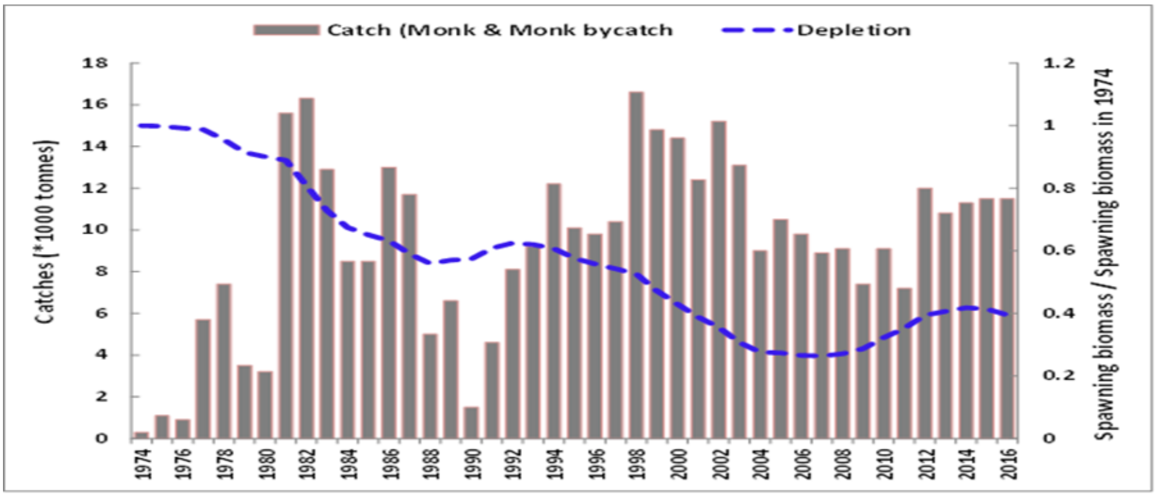


Figure 1: The estimated decline of the spawning stock biomass with the catches taken by the monkfish fleet and by other fisheries as bycatch from 1974-2016. Source:(MFMR.2016)

2.5 Background on the FLR package and a4a model used on Namibian monkfish

The Fisheries Library in R (FLR) is a collection of tools for quantitative fisheries science, developed in the R language, to simplify facilitation of the construction of bio-economic simulation models of fisheries systems as well as the application of a wide range of quantitative analyses (Nikolioudakis, 2007).

The FLR package builds on the powerful R environment and syntax to create a domain-specific language for the quantitative analysis of the expected risks and impacts of fisheries management decisions which is consist of the classes and methods to simplify the analysis. The classes and methods in FLR consider uncertainty an integral part of our knowledge of fisheries systems.

The FLR project has been developing and providing fishery scientists with a powerful and flexible platform for quantitative fisheries science based on the R statistical language. The guiding principles of FLR are open to all scientists who would like to contribute to the development of this useful and flexible package. The main purpose is to simplify the use of good quality, open source, flexible software in all areas of quantitative fisheries research and management advice (Nikolioudakis, 2007).

Within FLR, the statistical catch-at-age model A4a (Assessment 4 All) was developed by the European Commission’s Joint Research Centre (JRC) with the aim to develop, test, and distribute methods to assess large numbers of stocks in an operational time frame, and to build the necessary capacity/expertise on stock assessment and advice provision. Note that an environment like the one distributed by a4a promotes the exploration of different models for each process, giving the analyst a lot of flexibility. It also opens the possibility to efficiently include distinct models in the analysis. For example, a stock assessment using two growths, or several models for natural mortality could be performed. The main suggestion to streamline the assessment process is to combine the outcomes using model averaging (Millar, 2014) .Other solutions may be implemented, like scenario analysis, etc. What is important is to keep the data flowing smoothly and the models clear. (R Team, 2014) and FLR (Kell L. T.-M., 2007) provide powerful platforms for this approach.

2.6 Monkfish stock assessment in other locations

There is limited information on assessing monkfish by age-structured models because of the intensive input data to such models. Most of the regions claim that monkfish is caught as bycatch or caught by ghost nets, hence the available time series are too short to be fully informative (NEFSC, 2013)**.** Anglerfish (*Lophius piscatorius* and *Lophius budegassa*) are assessed separately but managed under a single TAC. Assessments for these species in the region of North-western waters do not occur for two reasons, biological uncertainty over aging data and lack of reporting of data. The standard method of ageing fish is to count the rings in the fishes' otoliths (ear bones). However, with angler and monk fish there is uncertainty on the number of growth rings laid down each year so no age information is available and age-based assessments cannot be conducted. The studies that have been carried out have shown that the stocks are healthy and increasing, but much more research and a detailed stock assessment is needed (Guide, 2018).

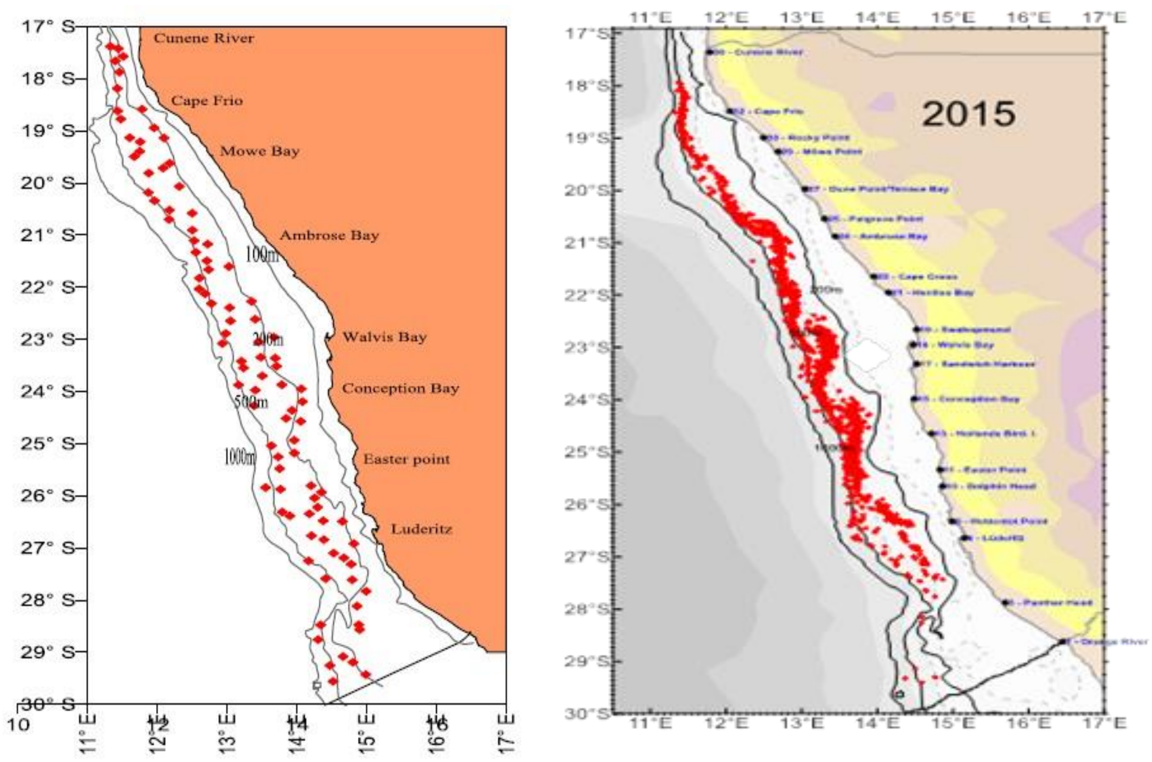
3 MATERIAL AND METHODS

Secondary data analyses were done for the purposes of importing data or parameters into the stock assessment models. This information was either previously completed during preparation for the ASPM input or independently performed for the a4a model. To do so, this study uses published and unpublished data which were gathered from the National Marine Research and Informaton Centre (NatMRIC) in Namibia.

The sets of data used include the following:

a. Age, length, maturity, and weight data from monkfish-directed surveys used to estimate parameters from a length-weight relationship and Von Bertalanffy growth equations as well as a maturity ogive (maturation information was based on females only: Table 1, Tables A1 & A5 in the Appendix).
b. Total nominal annual catches in tons of monkfish from Namibian waters 1991-2016. This is the trawling information recorded by vessel captains during fishing (Table A2).
c. Total annual landings in tons of monkfish from Namibian waters 1994-2016. This information is recorded by fisheries inspectors at the ports (Table 2).
d. CPUE indices: CPUE indices (Table 7) based on bottom trawl fleet logbooks from 1991-2016. This is the total catches of monkfish from hake and monkfish fleets.
e. Annual monkfish biomass indices from hake-directed surveys before commencement of monkfish directed survey (1994 to 2016), and annual monkfish-directed survey indices with CVs from 2000 to 2016 (Tables 3 & 4).

The area coverage of monkfish (*Lophius vomerinus* and *L. vaillanti*) commercial catches and surveys are shown in figure 2 (R Team, 2014). All surveys were conducted in the same way and the survey samples were collected from 94 predetermined stations using an optimised geo-statistical stratified random design method, from the Orange River (29°S) to the Cunene River (17°S). The commercial trawling area is within the 200-nautical mile EEZ for Namibia.



(a) **(b)**

Figure 2: a) Layout of Namibian monkfish survey stations and b) the entire commercial fishing area (Source: MFMR, 2015)

3.1 Running stock assessment models

3.1.1 Input data

These analyses use bottom trawl survey data and commercial catch data that were collected in the period 2000–2016 and 1991 to 2016 respectively. In 2006 no monkfish biomass survey was conducted due to delays in the tendering process as the contract of the company manning the research vessel had then ended. The 2017 survey data were not available as the monkfish survey is conducted in November each year. For the a4a model, year-specific mean weights at age, and maturity ogive models were calculated. For the ASPM, this study used the same, weight-at-age and maturity data as were used for the monkfish 2017 assessment, which were calculated by scientists at NatMIRC for both survey and commercial data. Both natural mortality and selectivity per age were set externally in ASPM and in the a4a model, as M = 0.25 and knife-edged selectivity beginning at age 2 respectively. Selectivity is constant per age through all the years in the ASPM model while a4a selectivity vary per age every year. In both cases, these data are used to specify the model but are not estimated.

Both survey and commercial indices were available and used in both models. For the a4a model, age and length data from the monkfish-directed survey were used to form year-specific age-length keys (ALKs) during the course of this study, but for the ASPM model, the ALK was generated by scientists at NatMIRC. In the a4a model, the ALK was used to calculate the numbers at age from numbers at length for all years, which were used as age-specific survey abundance indices. In contrast, the survey index was summed over all ages within years for the ASPM. To give information on surveyed age frequencies in the ASPM, catch-at-age (CAA) proportions were an additional input, calculated using ALKs by scientists at NatMIRC. For the a4a model, landings were also broken down by age groups using the same ALK as was used for the a4a survey data. In contrast, landings were inputted to the ASPM as a single sum per year over ages, but an additional data source of CAA proportions within landings was also inputted, calculated using ALKs by scientists at NatMIRC.

Commercial CPUE data were inputted to both models in the same manner, using the same CPUE index as was used for the most recent ASPM-based stock assessment. In the next section, alternate methods for standardising monkfish CPUE are illustrated, but their utility as alternate input data within the ASPM and a4a models will be explored at a later time.

3.1.2 Standardising monkfish CPUE as an index of abundance

Monkfish commercial data are available from 1991 to 2016 and recorded in daily log sheets. In this study only, data from 2000 to 2016 were used due to many irregularities that were found in data from the period 1991 to 1997. In January 1997, revised daily catch logs were introduced; these included a request for additional trawl information, such as geographical positions, start and end time of each trawl, seabed and trawl depth for each trawl, and target species (Maartens & Booth, 2001). The monkfish is assessed in total considering the targeted monkfish fishery and incidental catch (bycatch) in hake fishery. For each daily record unstandardised CPUE was calculated using the following formula:

$$CPUE = (\sum Catch / \sum Hours\ trawled) \qquad (1)$$

T reflecting the sum of catches trawled divided by total trawling time in a specific area. This relationship can be derived from the catch equation that relates catch, fishing effort and stock abundance

$$C = q\ N\ E \qquad (2)$$

where C is the catch, q the catchability coefficient, related to the efficiency of the gear, N the stock abundance and E is the fishing effort. Rearranging this equation reveals how CPUE is an index of relative abundance that is related to stock abundance via q:

$$C/E = q\ N \qquad (3)$$

The calculated unstandardised CPUE, which had an exponential distribution, was transformed into a normal distribution by a natural log transformation. This transformation was checked by plotting a histogram of before and after transformation using a GLM model. After the quality control process was completed the researcher proceeded with GLM model fitting.

3.1.3 Stock assessment using the ASPM in ADMB framework

The ASPM was developed in 2001 and has been used since then annually to assess the monkfish stock in Namibia. The ASPM uses the observed catch at age and an assumed natural mortality to determine the abundance of each cohort from one year to the next. Each cohort is initialised via a Beverton-Holt stock-recruitment relationship, where each recruitment is allowed to deviate according to a log-normal distribution with an externally specified standard deviation. The fishing selectivity and survey selectivity were assumed to follow parametric functions. Model parameters (stock recruitment function parameters together with annual deviations from this relationship, multiplicative error parameters, and yearly fishing mortalities) were estimated by penalised maximum likelihood. The negative log-likelihood function was minimised with respect to the unexploited equilibrium spawner-biomass (K^{sp}). The K^{sp} for the values of q ranging from 0.5 to 1.1 in steps of 0.05, resulting in 12 different model results. Steepness and recruitment were estimated within the model by using the information inherent in the catch-at-age matrix. The input data used in this model assessment covered the period 1974-2016 (Table 2). Aggregation level indicates whether data were constant over years or changing annually as well as whether data were aggregated across ages.

Table 1: Input data to ASPM in ADMB framework.

Data	**Units**	**Time range**	**Aggregation**
Commercial CPUE	kg/h	1991 -2016	annual, across ages
Survey estimates	tonnes	2000 -2016	annual, across ages
Total catch	kg	1974 - 2016	annual, across ages
Error parameter		2000 - 2016	annual, across ages
Weight	kg	1974 -- 2016	constant, by age
Maturity		1974 -- 2016	constant, by age
Selectivity		1974 -- 2016	constant, by age
Survey CAA	proportion	2000 -- 2016	annual, by age
Commercial CAA	proportion	1996 -- 2016	annual, by age

Table 2:Input data for a4a Model in FLR framework.

Data	**Units**	**Time range**	**Aggregation**
Commercial CPUE	kg/h	1991 -2016	annual, across ages
Survey estimates	tonnes	2000 -2016	annual, by age
Total catch	kg	1974 - 2016	annual, by age
Mean weight	kg	1974 -- 2016	annual, by age
Maturity	proportion	1974 -- 2016	annual, by age
Selectivity	proportion	1974 -- 2016	constant, by age

3.1.4 Stock assessment model using a4a model in the FLR framework

The approach was split into 4 steps: the first step started with converting numbers-at-length and mean-weight-at-length data to age data to the numbers- and mean-weight-at-age data using the ALK. This step also included modelling female maturity using a GLM with binomial error and logit link function to obtain proportions mature at age (i.e., a maturity ogive and the model parameterisation was chosen to have age- and year-specific fishing mortality, age-specific catchability, and a B-H stock recruitment relationship. The third step was fitting the age-structured assessment model using these data as input.

In step 1 and 2 there was no fitting of growth models or natural mortality models. The rationale for providing mean-weight-at-age keys instead of model output was to provide tools that allow any deviations associated from the modelled processes to be carried on into the stock assessment, e.g. through lower-than-expected mean weights young ages. Natural mortality was held constant to be consistent with the ASPM model and to avoid confounding with fishing mortality and recruitment (Punt et al. 2014).

The input data in the model are listed in Tables 2 & 3. After model fitting, short-term projections were made and biological reference points calculated, which are dealt with by the FLR packages FLash and FLBRP (Kell , 2017). The flow of data from the four steps within the FLR framework, including the classes of the R objects that carry the data (in black) are shown in Figure 3.

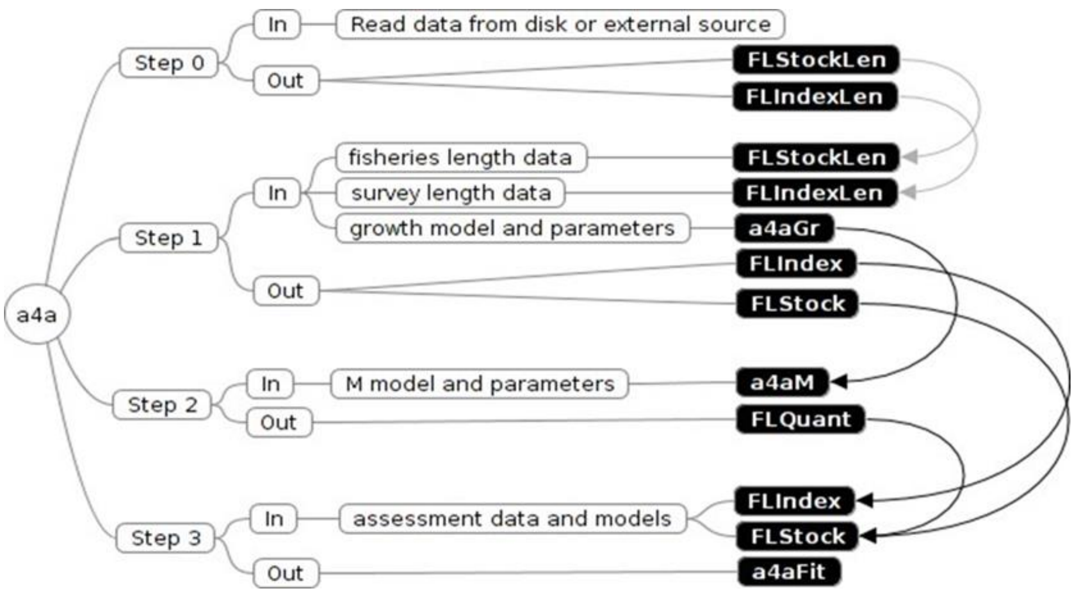


Figure 3: In/out process of the a4a approach. The boxes in black represent the classes of the objects that carry the information in and out of each step. Source: *(Ernesto et al, 2014).*

It is worth noting that the available survey index of abundance by age only covers the last few years of the fishery (2000-2016), although catch-at-age data is available from 1996. This is likely to complicate matters, as trends in population abundance and fishing mortality prior to 2000 will be estimated based almost entirely on trends in catch-at-age, which are likely to be affected by changes in fishing effort, targeting and other factors not related to stock status. The objective function of the model minimises the negative log likelihood by finding the parameters that make the data and the model predictions as close as possible in terms of squared deviations.

Table 3:The input data in the a4a model are listed in the table below

Input data	Survey	Commercial
Age -length	√	
Catch at Age	√	√
Numbers at Length	√	√
Total Landings		√
Weight at Age	√	
Survey CV	√	
Maturity at age	√	

3.2 Analysis of model fits and comparison.

An important difference between the two models is that in ASPM, models are run independently with different catchability values (q) and each model will have individual results. In the a4a model, catchability is age-specific and estimated when minimizing the negative log likelihood. For comparison, the fit of q = 0.5 was compared to a4a, as this was the one used for management advice in the most recent stock assessment. The model fits were analysed to test and measure the strength and flexibility of each model in estimating the growth parameter and stock indicators of monkfish. The quality of each model fit was inspected by looking at the residuals in diagnostic plots.

3.3 Analysis of stock status and projections

Stock status resulting from the models are compared in terms of the final year values of spawning stock biomass (SSB) and fishing mortality (F), as they relate to the theoretical values of those expected when maximum sustainable yield is being generated at equilibrium (SSB_{msy} and F_{msy}). The Kobe process is a way of summarising stock assessment results in a graphical way that has become widely used (restrepo, 2011). On the x-axis, the plot represents biomass (or spawning biomass), expressed relative to B_{MSY}. And, on the y-axis, it represents fishing mortality relative to F_{MSY}. The plot offers a simple way in which managers can quickly infer if the stock is in good or bad shape, depending on where it falls in one of four quadrants in the plot. A value below 1.0 on the x-axis means that the biomass is below B_{MSY} , Regional Fishery Management Organizations (RFMOs) refer to this as the stock being overfished. And, a value above 1.0 on the y- axis means that the fishing mortality is above FMSY (meaning that the stock is being overfished or that overfishing is occurring) (Restrepo, 2011). A Kobe plot was done to compare the two models Projections were also done for three years in a4a model and for one year in ASPM model. The stock status was analysed and then the recommendations were made.

4 RESULTS

4.1 Running stock assessment models

4.1.1 Input data

The mean weight per age was similar for all years from 2000 to 2016 except for 2010 where n weight by age was higher a than in other years in the series (Figure 4).

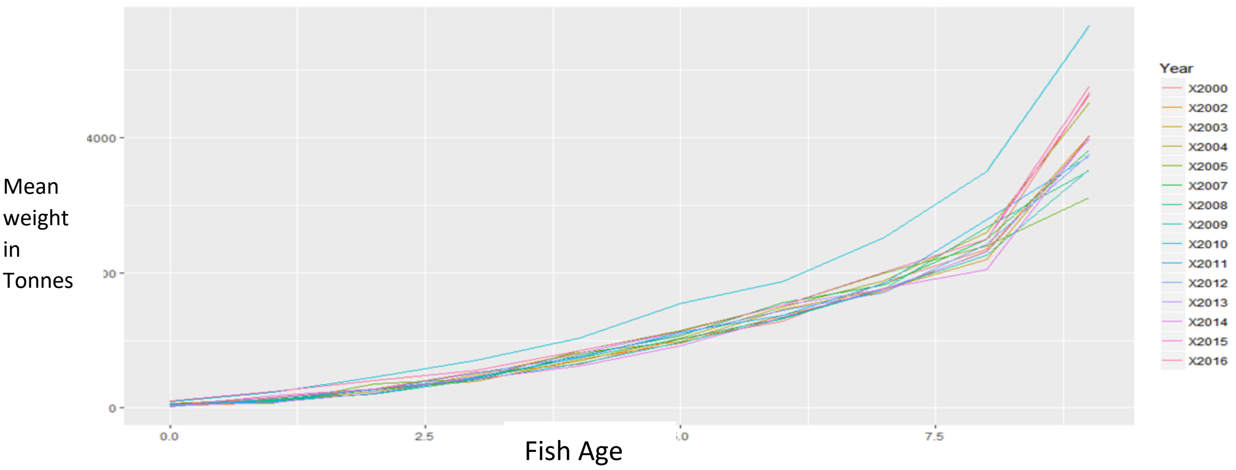


Figure 4**:** The mean weight per age across the years from 2000 to 2016.

Maturity at age was predicted from fitting logistic curves to the proportion of mature individual in each age group. Results vary substantially across years, especially for the maturity data from 2003 when monkfish seemed to reach sexual maturity in their sixth year (Figure 5).

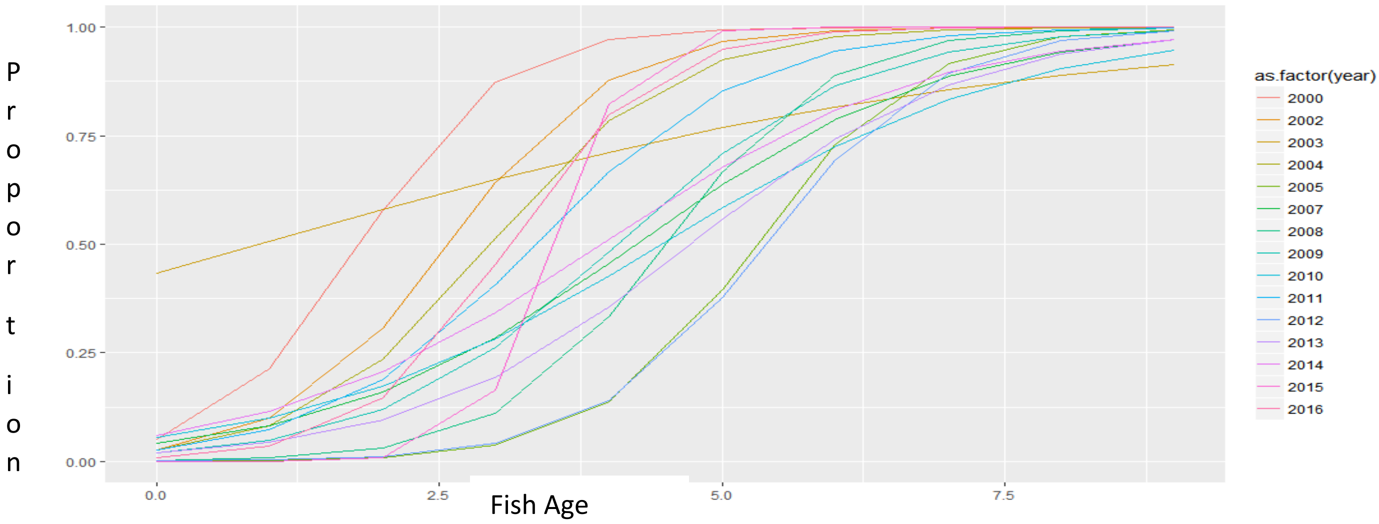


Figure 5: Predicted maturity proportions at age for all year (2000 to 2016).

Number per age of monkfish (converted from mean number per length using the ALK) varied substantially from year to year. A high number of age 0 to age 3 were recorded in year 2010, which is a good indication of the recruitment during 2008, 2009 and 2010. In other years the same ages were stable with drop in year 2004 of age 3. However, the same ages were stable in recent years (e.g. 2016).

Age 4 to age 7 were high in 2015 indicating a sign of recruitment in past years with few old fish caught in 2015. Age 9, which is an aggregation of all older ages, show that in general there are more old fish.

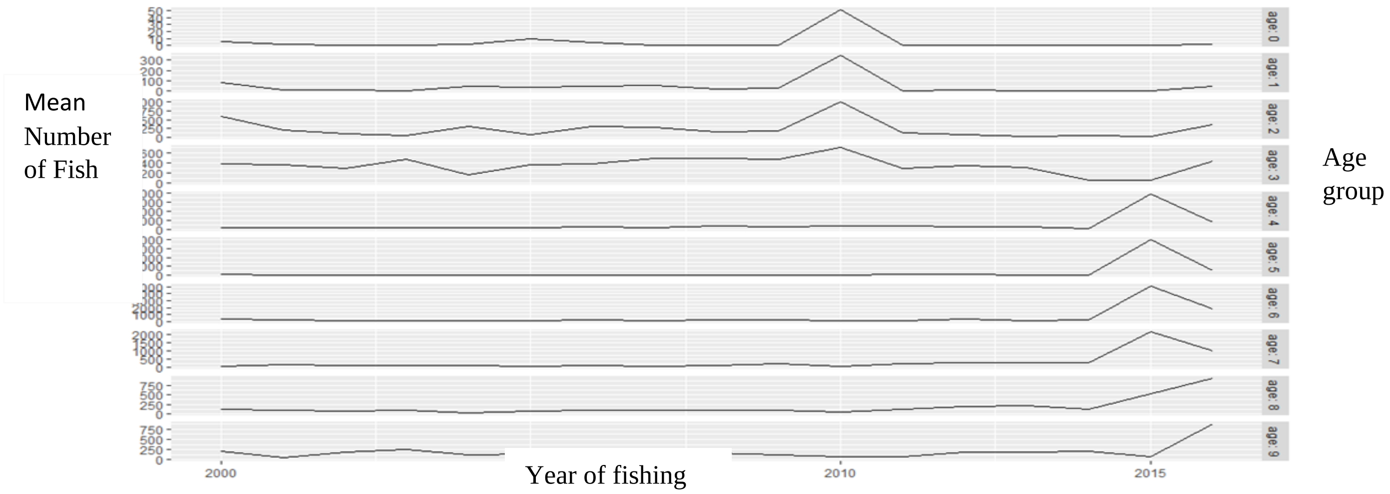
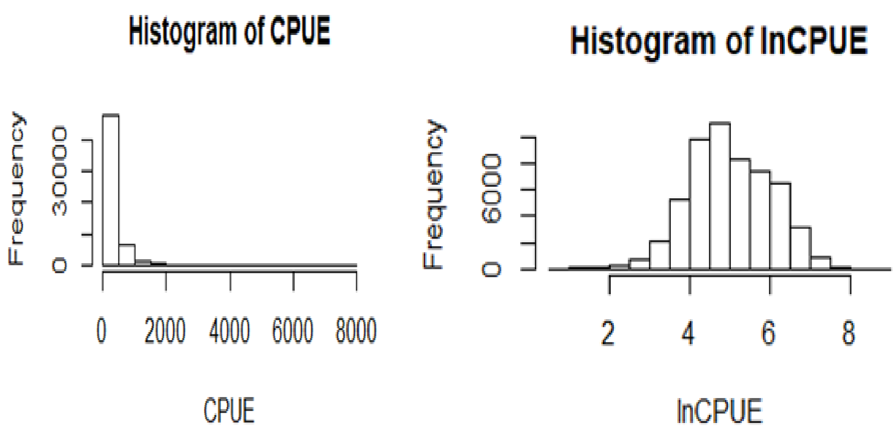


Figure 6: The number indices per age across the years from 2000 to 2016.

4.1.2 Standardising monkfish CPUE

The monkfish CPUE was not normally distributed. The figure 1((a), (b)) below shows the monkfish CPUE before and after log transformation, figure 1(b) indicates the mean lnCPUE was normal distributed with the mean value of around 5. In general monkfish CPUE seems to be skewed to right due to fact that zero catch can be justified than the extreme high catches.



(a) (b)

Figure 7:(a), (b): Mean monkfish (2000-2016) CPUE histogram before the CPUE were transformed and lnCPUE after log transformation.

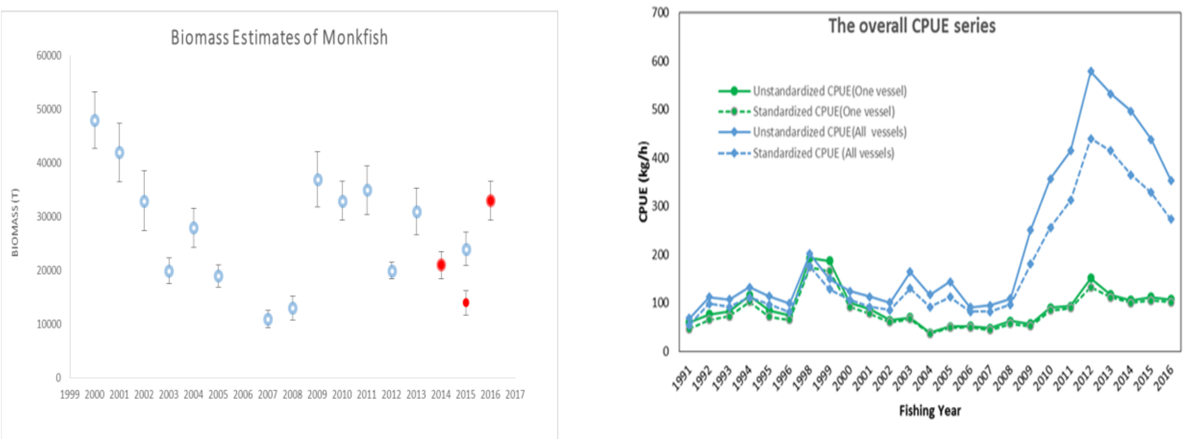


Figure 8: Index of abundance estimates for annual survey (2000-2016) and commercial CPUE (in (kg/h)) for the Namibian monkfish (1991-2016) after standardisation by the GLM.

Thirteen possible GLM models were run for the commercial data as an attempt to explain the variation found (Table 3). The listed variables were combined in order to compare how much variation is explained per variable used. More specifically, the purpose of model building was to get a simple/minimal adequate model that used fewer variables while explaining more variation in the data. When GLM was fitted to catch rate data, factors that have significant effects and the extent to which they influence results can be identified through the analysis of deviance of the GLM and can then be standardised.

The amount of variation explained by each of the explanatory variables in the model is indicated by r^2 in the table below while the model fitting is indicated by AIC values. All model results are given in table 3 where all monkfish fleets active on the fishing grounds are considered. The explanatory variables that account to most of the variance in these data for single parameter models are vessel ID and GRT ($r^2_{adj} = 0.43$). The monthly variation accounts for 2.3% of the total variation. The annual interactions with month are averaged for all the years. The model that explain highest percentage and has smallest AIC value=112268, was LnCPUE ~ μ +Year+Lat+GRT+ ε (M7). The best model (M7) accounts for 57.0% of the total variation in monkfish CPUE. The model with interactions (M12 and M13) could not improve the percentage explained in the model.

Table 4: List of GLM model specifications. The models are listed in the order they were run and not necessary in order of their performance /fit.

Model	Model specification	R^2	AIC	AIC-minAIC
M1	LnCPUE ~ μ +Year+ ε	0.324683	136938	24670
M2	LnCPUE ~ μ +Lat+ ε	0.01696	157784	45516
M3	LnCPUE ~ μ +GRT+ ε	0.43261	127323	15055
M4	LnCPUE ~ μ +Month+ ε	0.022923	157444	45176
M5	LnCPUE ~ μ +Depth+ ε	0.004285	158488	46220
M6	LnCPUE ~ μ +Year+Lat+ ε	0.333459	136235	23967
M7	**LnCPUE ~ μ +Year+Lat+GRT+ ε**	**0.567583**	**112268**	**0**
M8	LnCPUE ~ μ +Year+Lat+GRT+Depth+ ε	0.333459	136235	23967
M9	LnCPUE ~ μ +Year+Lat+GRT+Month+ ε	0.517217	118351	6083
M10	LnCPUE ~ μ +Year+Lat+GRT+Depth+Month+ ε	0.354717	134456	22188
M11	LnCPUE ~ μ +Year+Lat+GRT+ ε	0.38482	132186	19918
M12	LnCPUE ~ μ +Year+Lat+GRT+Year*Month+ ε	0.38232	756117	643849
M13	LnCPUE ~ μ +Year+Lat+GRT+Year*Lat+ ε	0.39509	131274	19006

After choosing the best model, the overall model fit and appropriateness regarding the subset of regression parameters were tested using a likelihood ratio test (LRT). Likelihood ratio tests are similar to partial F-tests in the sense that they compare the full model (Model 2) with a restricted model (Model 1) where the explanatory variables of interest are omitted (the intercept model). The p-values of the tests are calculated using the 2 distributions. A likelihood ratio test comparing the full and reduced models can be performed using the R anova() function with the additional option test ="Chisq". The likelihood ratio test statistic is =18682 with a p-value=2.2e^-16. Hence, we have relatively strong evidence in favour of rejecting H_0 (the null hypothesis intercept model).

Table 5: List of GLM model specifications. The models are listed in the order they were run and not necessary in order of their performance /fit.

Analysis of Deviance

Model	Resid-df	Resid Dev	Df Deviance	Pr(>Chi)
1: lnCPUE ~ 1	55547	56479	0	
2: lnCPUE ~ as.factor(Year) + LatDeg + GRT	55526	37797	21	18682 < 2.2e-16 ***

The best model (M7) accounts for 57.0% of the total variation in the CPUE and therefore the GLM analysis was based on model (M7) results (Figure 20 in Appendix). However, this was not used in the assessment, because for the models to be comparable, the data set should be same. For that reason, standardized CPUE used in the last assessment year were used instead.

4.1.3 Stock assessment using ASPM model in ADMB framework

Index of abundance fits by the ASPM in ADMB framework are shown in the figure below. The model overestimated the survey while the commercial CPUE was underestimated by the model, especially in the last 7 years. Most of the data in the CPUE around 2000 to 2009 fit the model very well.

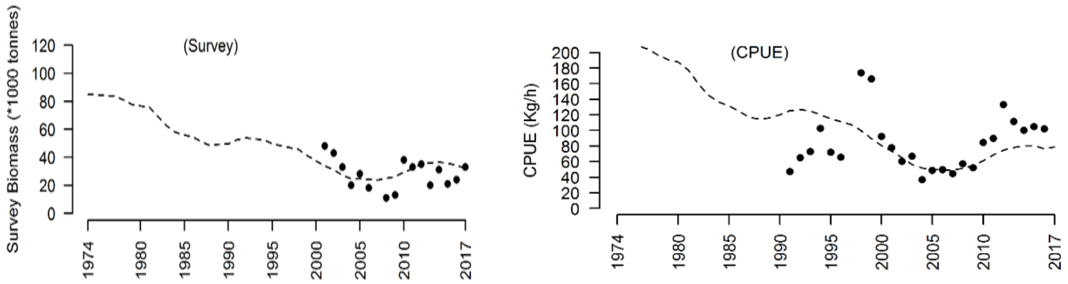


Figure 9: Model fits to the observed swept-area survey biomass estimate on left panel and observed CPUE on right panel (Source: MFMR 2017).

The catch at age proportions, which were converted from catch at length, was used to fit the model from for survey and commercial sources respectively. The year 2003 has the best fit for the survey data (CAAI). There was consistency in fits throughout all the years. For the general model, the fit was not bad even though there was some overestimation and underestimation of proportions at age among years. The commercial data (CAA_I) showed a similar trend. There was a noticeable age difference in the survey and commercial graph. The survey traces the recruitment while the commercial is expected to catch fish older than age 1. The survey (CAAI) recorded high proportions of smaller fish as the survey supposed to tract the information on recruitment whereas the commercial fleet consistently had a large proportion of age 8 fish in both the data and predictions.

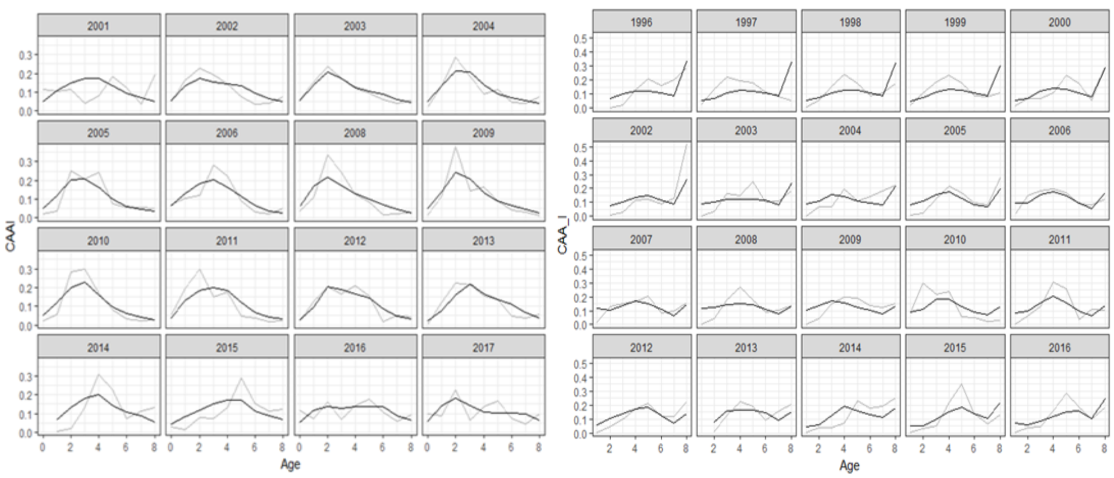


Figure 10: Length-frequency diagnostic plots from ASPM estimate.

Recruitment estimation from 1996 to 2017 is shown in Figure 11. These recruitment values are derived from the observed catch-at-age proportion data, which relate age-frequency information. The estimated recruitments were higher than the long-term average (1996-2017) during the period 2006 to 2011, hence the stock grew faster in successive years. The recruitments for 2016 and 2017 are also above the long-term average. The residual patterns indicate that the Beverton and Holt model does not adequately describe stock recruitment relationship for *L. vomerinus*, as recruitment does not appear impaired by low spawning stock biomass.

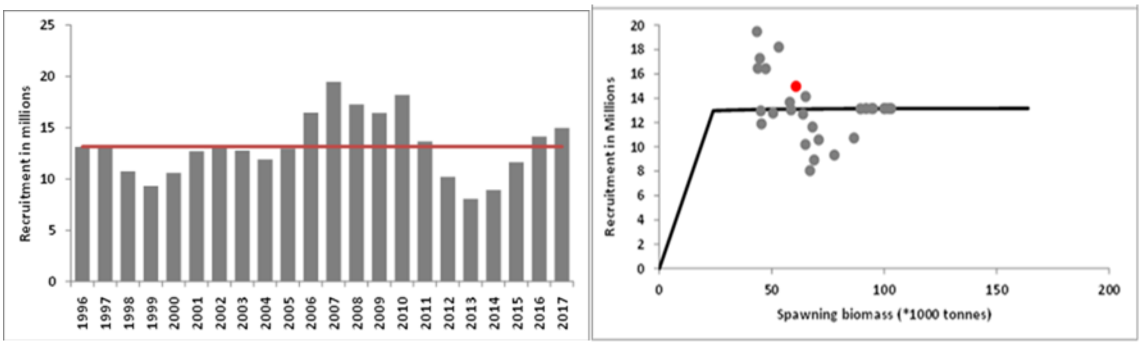


Figure 11: Estimated recruitment and Beverton-Holt stock recruitment curve from ASPM model.

4.1.4 Stock assessment model using a4a model in FLR framework

The index of abundance from commercial CPUE as estimated by a4a model is compared with observed series with confidence intervals is shown in figure 12. The observed commercial CPUE indicated by the black line and the blue line indicate the estimated commercial index by the model. The fit shows that the CPUE is increasing for 2016 and is around 118 kg/h. The grey area shows the 95% confidence interval, within which the fitted values mostly fit.

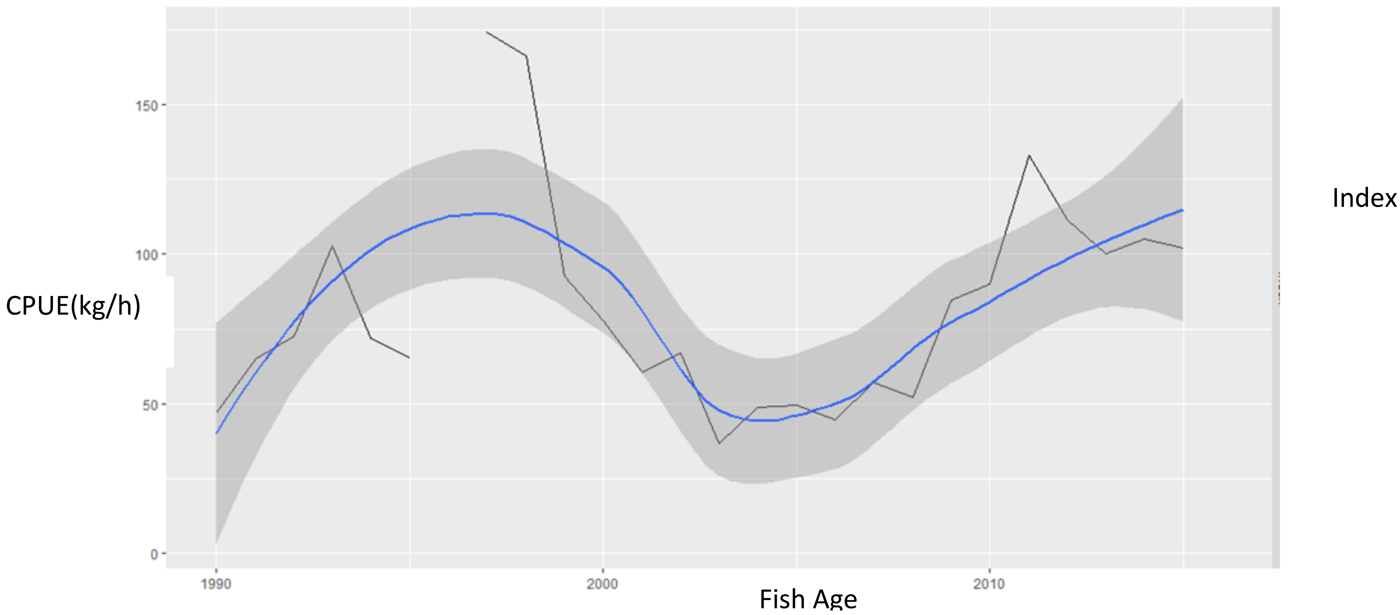
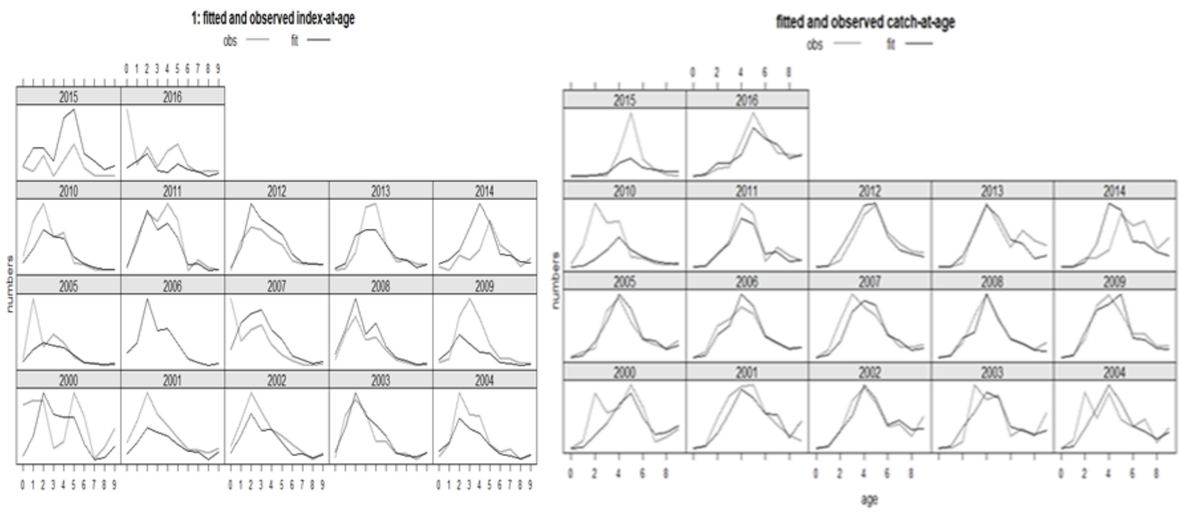


Figure 12:The observed CPUE and estimated CPUE with the 95% confidence interval.

The fit to age frequency information can be found in Figure 13. Most of the year was underestimated by the model in the survey data (number) compared to the same year in the commercial (number). In other years, the model tends to under-estimate the younger ages (age

0 to age 4) and fit better with the older ages (age 6 to age 9+) in both survey and commercial data.

Most of the data fit the model well, while 2000 and 2015 are showing a worst fit. The model underestimated the data in 2010 and 2015, in which the 2010 model underestimated the younger age (age 0, 1, 2, and 4) while in 2015 the model underestimated the middle age (from 2 to 6). Hence, most of the younger age groups are under-estimated by the model.



(a) Survey (b) Commercial

Figure 13((a),(b): The observed and fitted catch at age for Survey data and the observed and fitted index at age for commercial data.

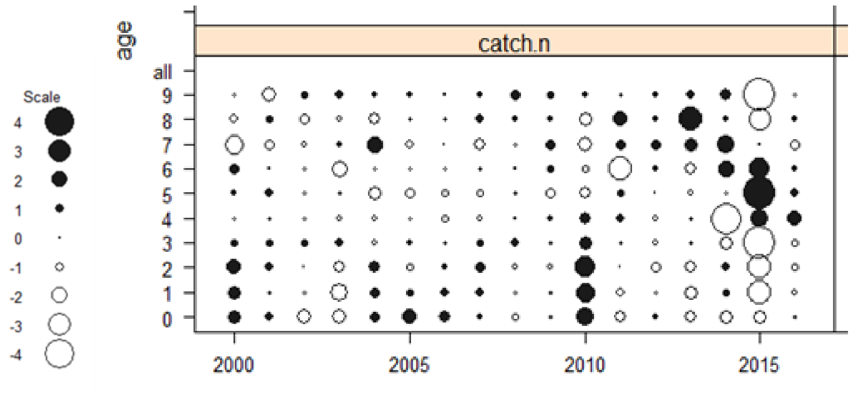


Figure 14: The residual plot of catches at age. The bigger the circle the greater the difference between observed and fitted, and the smaller the circle the lesser the difference. While the empty circle indicated values where the model overestimated the value and dark circle represent where the model underestimated the catch at age.

Recruitment and the Beverton Holt spawning stock biomass are estimated by a4a model (figure 15). The blue line is the estimation line in all the figures and the grey line indicates the 95% confidence interval. The first plot shows the estimated recruitment against the stock spawning biomass and the red line.

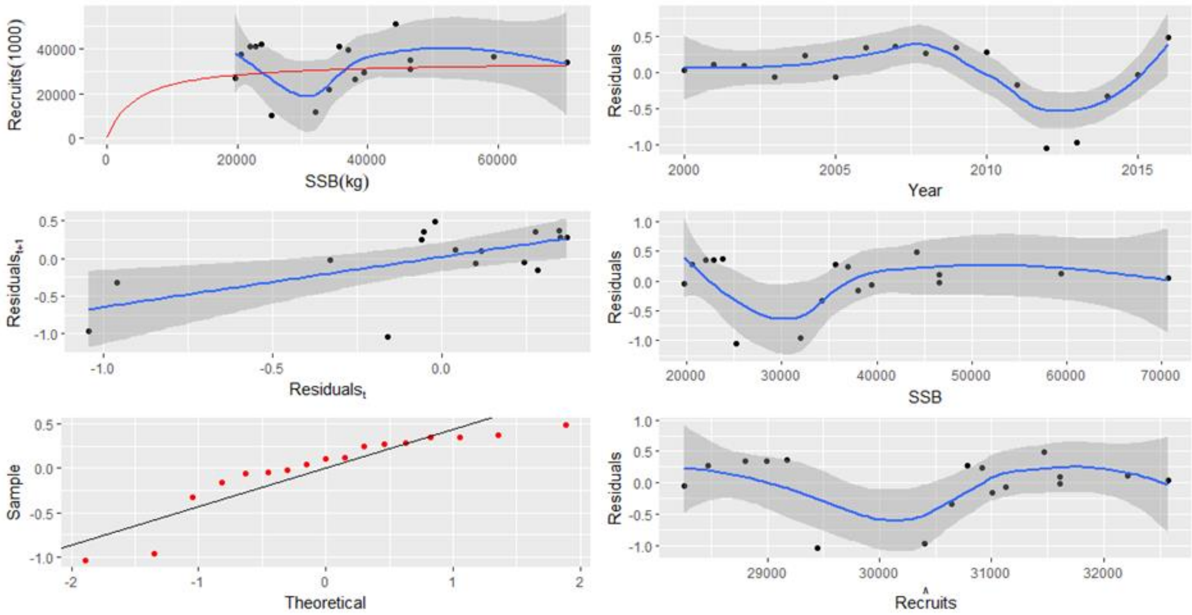


Figure 15: Recruitment and the Beverton Holt spawning stock biomass and the residual plot. The blue line is the estimation line in all the figures and the grey line indicates the 95% confidence interval. The first plot shows the estimated recruitment against the stock spawning biomass and the red line.

4.2 Comparison of stock status and projections between the two models

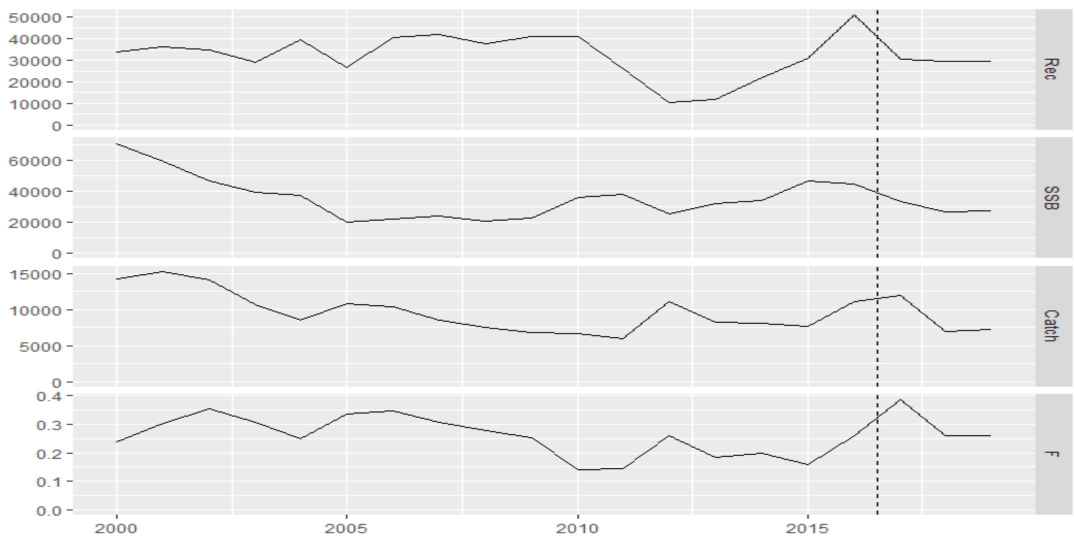


Figure 16: Short term prediction for the next three years.

The four panels illustrate different estimations from the model, namely Recruitment, Spawning Stock, catches and fishing mortality (Figure 16). These recruitment values are derived from the observed catch-at-age data. The estimated recruitments (in millions) are estimated to be similar for all years from 2000 to 2015 with a sharp increase from 2015. Next panel in the figure shows the stock spawning biomass (4000t) which is estimated to have declined from 2000 to 2005 and subsequently stabilised for almost five years. For 2016 it is 49 thousand, and the 2015 to 2017 SSB was estimated to be declining. The catch and fishing mortality have been high and unstable in recent years and is estimated to be around 30% for 2017.

Short term model predictions from the a4a model, following the dotted vertical line (years 2017 -2019), are given in figure 16. The prediction shows a decreasing trend for all estimated values from 2016 and constant prediction for 2018 and 2019 respectively.

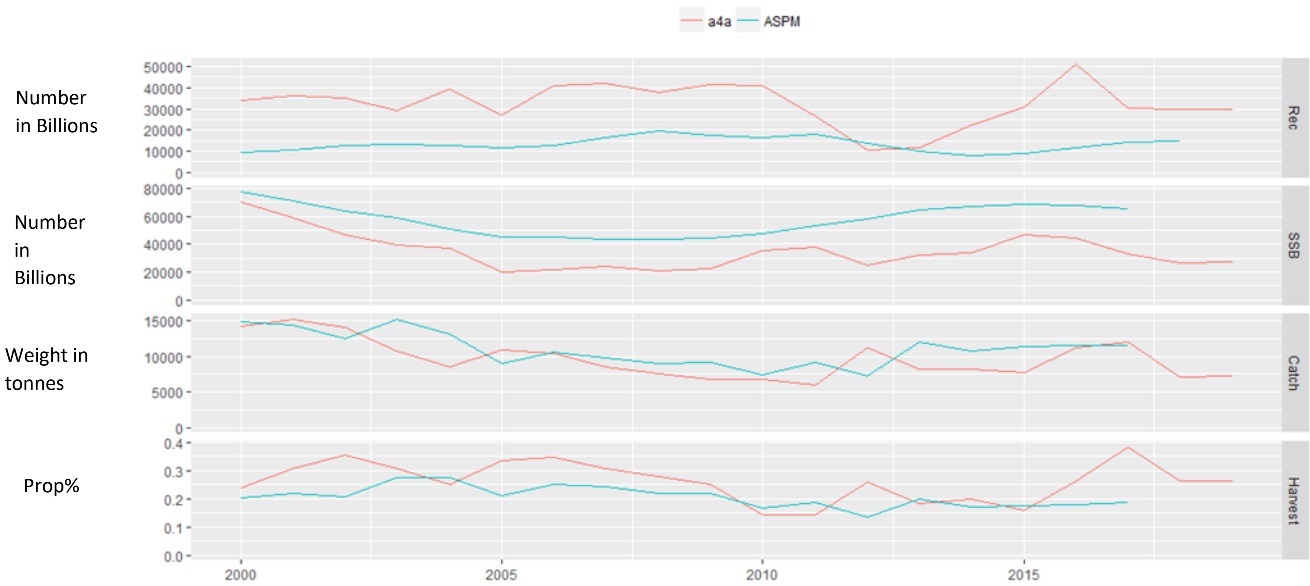
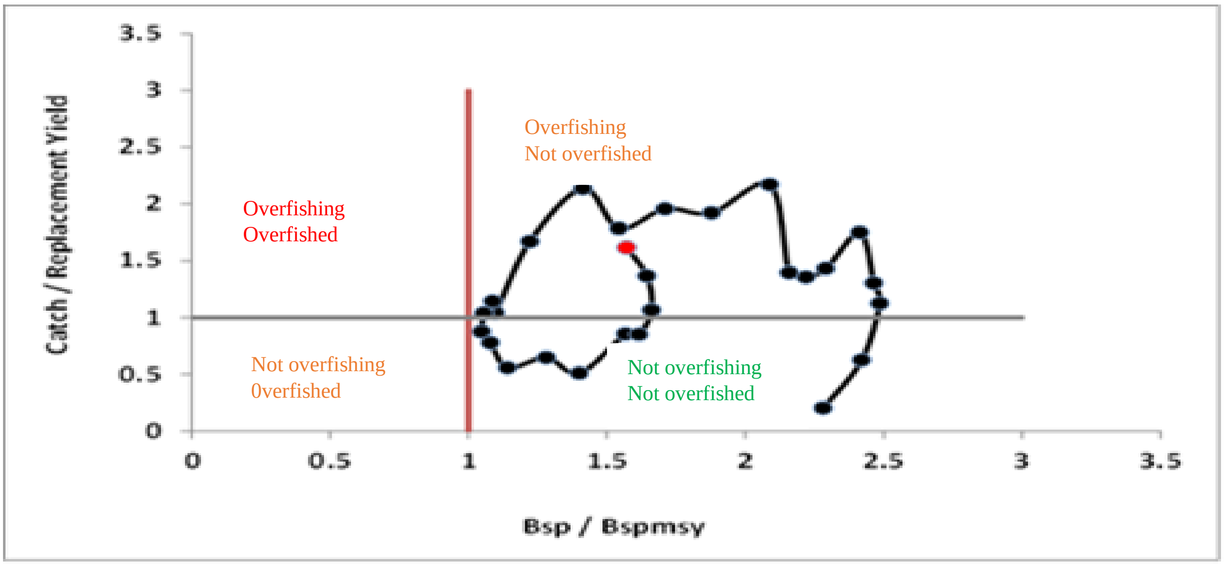
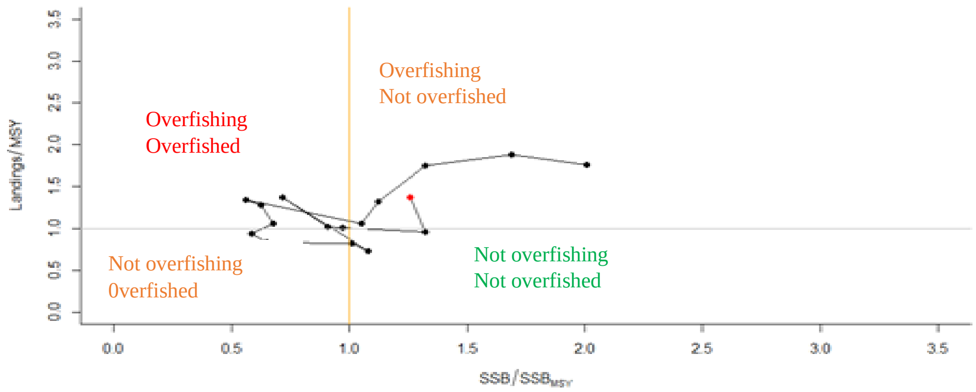


Figure 17: Estimated recruitment, SSB, catch and fishing mortality for Namibian monkfish, using a4a model and the ASPM model.



(a) Kobe plot of ASPM model



(b) Kobe plot of a4a model

Figure 18 ((a);(b)): The Kobe plot for the two models.

The estimates of recruitment from the two methods are shown in Figure 17. The trend in the recruitment pattern is relatively similar between models except for the last two years. While the results from a4a estimates a high recruitment that is unstable for all years except 2002 peaks in 2016. The ASPM model shows a more stable smooth recruitment throughout the years but has overall lower values than the a4a estimation.

The spawning stock biomass estimations are also shown in figure 19. The two models, a4a and ASPM give a similar trend of spawning stock biomass. ASPM model estimations are higher in magnitude than the estimations of a4a throughout the series, unlike the estimation of recruitment. Both models indicate a relative decrease from 2005 to 2010. The ASPM model estimated the spawning stock biomass to be around 70,000 tons for 2016, while a4a estimating it to be around 40,000 tons for the same year.

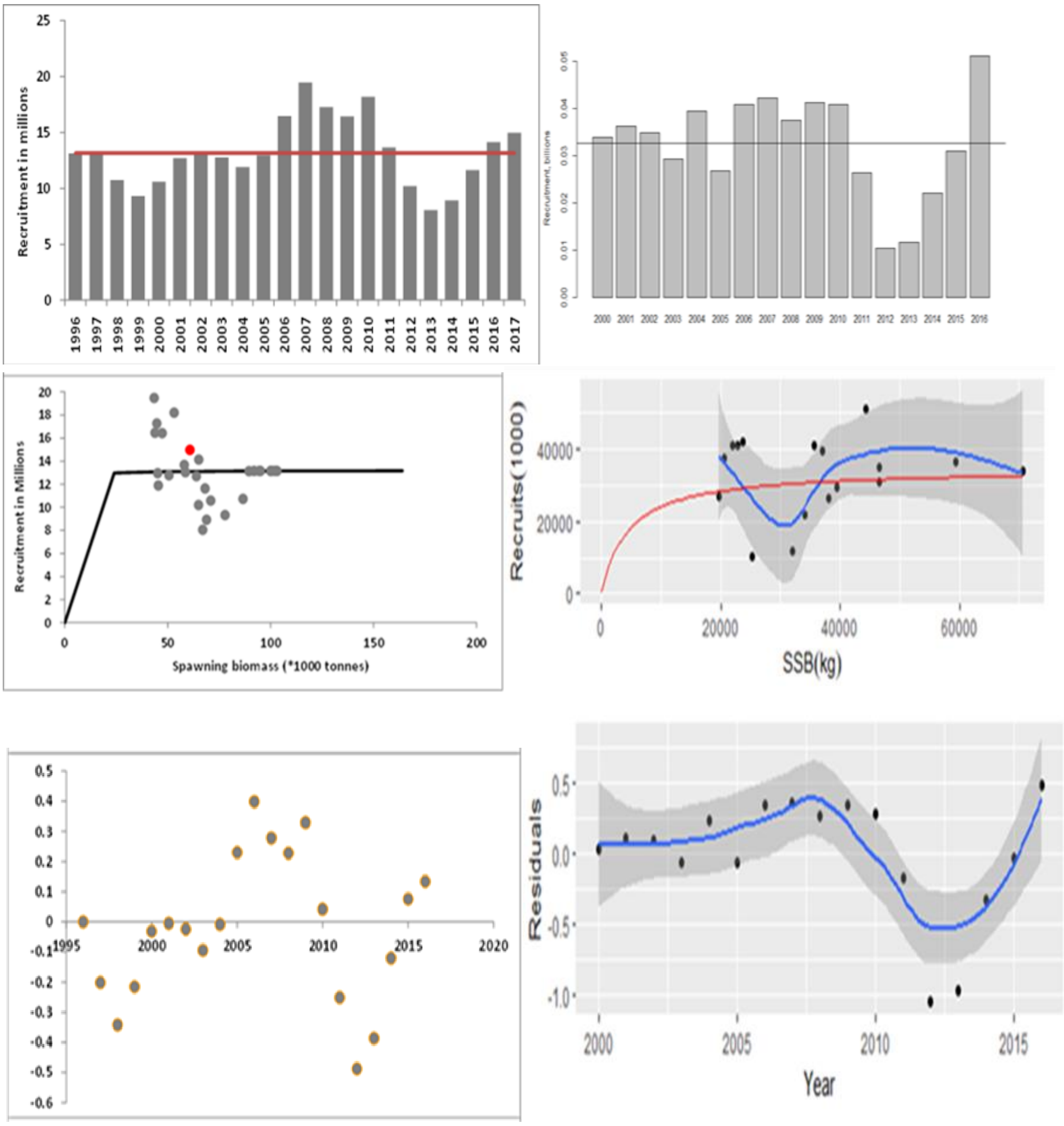


Figure 19: Comparison of estimation recruitment, S-R relationship and yearly residuals.

5 DISCUSSION

Both the ASPM and a4a models are age structured. The importance of including age structure in population dynamics models is that the stock can be assessed with respect to patterns in growth and recruitment. In contrast, growth and recruitment cannot be tracked in models without age or size structure.

Although both the ASPM and a4a models ultimately rely on the same survey and commercial data, the data processing for import into the two models were quite different (Table 1 and Table 2). Maturity and weight at age (figure 4), were constant over years in the ASPM model, whereas they vary by year in the a4a model, as they were recalculated from that year's survey data. The maturity at age among years appears to show autocorrelation (i.e., any year's maturity pattern is more similar to surrounding years), except in 2003 which show that there were no immature fish caught that year (figure 5). Even though there were correlations among years, there was also observed variability especially among age 1 and age 6. This model also indicated that there was consistency in the general shape of maturity over age, which shifted left or right over ages among years. The year 2013 is an exception, because no younger fish were caught. It has not yet been confirmed if the data are missing or if this was due to observation/sampling error (figure 4). Differences between the models also exist in time ranges of data input.

Different forms of data were used to estimate model parameters and predict the numbers at age within both models (Figure 6). These data contain both age-frequency information and absolute abundance information for each year. For the ASPM, the age-length key, formed from survey data, was converted to catch-at-age proportions each year found in both the survey and commercial catches. These data reflect age-frequency information and were used as input data alongside the indices of abundance (survey indices and CPUE). The indices of abundance for the ASPM model were aggregated by year, so they only reflect a measure of relative abundance levels of the population, rather than age frequencies. In contrast, the survey and commercial catch data in the a4a were aggregated as numbers per age for each specific year (figure 9). As a result, both age-frequency and relative abundance information were contained within these data.

An important difference between the two models' results is how the abundance indices were used. Because the ASPM indices of abundance were aggregated over ages, within years, only a single catchability parameter (q) was estimated. The current practice with running the ASPM model is not to estimate the survey catchability. Instead, models were run independently with different set catchability values (q) and each model will have individual results. The Akaike information criteria (AIC) is then used to select the optimum model on which the assessment will be based. In the a4a model, the age-specific catchability parameters are estimated. In contrast, in the a4a model, catchability was age-specific and estimated when minimising the negative log likelihood. The difference in results of the two models is expected since the input data of each model goes under different data processing, for example ASPM model uses age length key while the a4a model convert age length key to number at age. As catchability parameters scale abundance indices to absolute levels of abundance, model results are heavily dependent on assumptions regarding catchability. For example, a population with a higher absolute abundance will yield a larger TAC, assuming that biology is the same between the two populations. An important task for the future will therefore be to further examine differences between the model related to catchability and re-evaluate the method used for choosing the best ASPM run among the runs that differ in fixed catchability values.

A benefit of using the a4a model is that plotting and editing of the plots is easily done in FLR. This differs from the ADMB framework, in which one needs to plot results in excel or in R. The design of the plots in FLR are therefore different from excel design, on which ADMB results were based. The greater accessibility of plotting in FLR facilitates diagnostic analysis, which enables the modeller to examine problems with the model fit or misspecification. For example, most of the uncertainty in both models is caused by inconsistencies in the data especial the younger age and older age. For example, the proportions of catch at age 8 are consistently high in both the ASPM data and predictions, but this pattern is not found in the a4a model. In addition, Kobe plots indicate that the ASPM model is the more optimistic model compared to a4a model because it does not reveal that the stock was overfished some years.

These differences between the models suggest that further studies should be done to determine the cause of differences. Further studies could include, for example, a review of the process of forming CAA proportions and assimilating them into the ASPM model, which could then be compared to the data input into a4a for major differences. It could also include the long-term predictions of both models to see whether the difference will be maintained between the two models.

The results of the a4a model were in some respects similar, and in some respects different from the estimates obtained from the ASPM model, which was used for the 2017 assessment. In the ASPM model, recruitment was expected to increase from 2015, spawning stock biomass was estimated to be stable and fishing mortality and catches were estimated to be high and unsustainable for the last three years. The survey index and CPUE from fishing fleet, indicated that the monkfish spawning stock biomass was decreasing. Taking these estimates into account, the model estimated a lot of variation in the 2015 most of them were underestimating the observed data. In contrast, that a4a model showed less variation between observed and fitted lines. In addition, a4a model could predict the confidence interval along the whole series which is a good measure of total variation in the fishing system.

The overall pattern in fishing (catches and harvest rate/fishing mortality) estimation by the two different models showed a similar trend but varied throughout the years (figure 17). The two modeling frameworks estimated the two indicators differently, since a4a estimated catch and the ASPM only took catch as exact removals of biomass from the population through time. The a4a gave mostly high fishing rates. ASPM gave higher estimation based on catches/exploitable biomass. The a4a model estimate of catch was close to the actual value of landings for 2016, shown under the ASPM results, which was around 12,000 tonnes. However, the two models gave different estimates of harvest/fishing mortality in the same year. The a4a model estimation for 2016 was above 0.35 and ASPM model fishing mortality estimate was around 0.25, likely as a result of the lower spawning stock biomass estimates found in the a4a model. The ASPM model seemed to estimate catches/landings higher than the a4a model. The a4a model estimated the fishing mortality to be relatively higher in most of the years with a fall in 2004, 2010 and 2015. Both models provided relatively good fits to the monkfish CPUE data. The three-year prediction that was performed by a4a indicated that if fishing effort continues at the same level as in 2016, fishing mortality will continue to be high, and the stock cannot sustain the fishing pressure, as it is this year lies in the ‘overfishing but not overfished’ quadrant of the Kobe plot (Figure 18). It is difficult to explain why the fishing mortality is high, as monkfish were fished as bycatch from hake fisheries and the directed fishery started in the late 90s. The two Kobe plots (Figure 18) of both models indicate the similar position of state of the stock which show that the overfishing is taking place, the stock is moving from a better quadrant (not overfished and no overfishing is taking place) to a risk quadrant. Current spawning stock biomass is above the spawning stock biomass at MSY and the catches are higher than the replacement yield (or catch at MSY). This likely happens because fishing mortality is estimated to be high and the spawning biomass relatively lower in the a4a model. The only difference between the two management plots is the fishing history. The ASPM model indicates that the spawning stock biomass was never below the corresponding value for fishing MSY at equilibrium, while the a4a indicate that the stock has indeed dropped below this reference point for several years, falling into ‘overfished’ quadrants (Figure 18).

One of the main objectives of a4a is to facilitate a risk analysis, by estimating the growth parameters and natural mortality so that scientific advice provides policy and decision makers with a perspective of the uncertainty existing in stock assessments and its propagation into the analysis of monkfish. The sources of uncertainty implemented so far are related to the processes of growth, natural mortality and reproduction (stock-recruitment), and with the estimation of population abundance and fishing mortality by the stock assessment model. In all cases the framework can include sampling error. Such a risk analysis, for example through management strategy evaluation, is beyond the scope of this study, but model results presented here are an important prerequisite for one. For example, the results of this study could be used in the future in a management strategy evaluation of a proposed harvest control rule.

6 CONCLUSION AND RECOMMENDATION

Fishing mortality and catches have been unstable and high throughout the series and increase as from 2015.The a4a model estimated the level of recruitment to be higher than the current level that is estimated by the current assessment model (ASPM). The residual diagnostics showed that the ASPM underestimates the population abundance levels of monkfish according to the CPUE data but overestimates it in relation to the survey data. The a4a model estimation however, remained in short range of the data. The two models estimated different MSYs. A4a predicted MSY to be around 8 tonnes, while the ASPM estimate MSY to be around 10. This is important for management; therefore, further studies should be aimed at analysing why these differences occur. For example, differences in data processing, data assimilation, length of data series incorporated, and parameters estimated (especially catchability) were evident, so both models should be run with these differences minimised to determine what causes major differences in model results. This task will require more detailed study on both ASPM and a4a models. As an example, the ASPM model should be run in ADMB with subset data. Further studies are needed to determine which model is better and how both can be used for management.

The estimates from the two short term predictions indicate that there will be a reduction in stock spawning biomass and recruitment, while the catches and fishing mortality will be higher than the current levels in the future (Figure 16). The Kobe plot indicated that the stock is in the same status quadrant (‘overfishing but not overfished’), even though the historical path of stock statuses between the two models was different. Future predictions show a further decline in biomass and catch if the current fishing levels are to be maintained. Any increase in fishing mortality exacerbates the situation.

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I dedicate my project work to my late sister who passed on while I was compiling this project, I am so sorry I could not be there during the last days of your life. I must acknowledge as well my many friends, 2017 UNU-FTP staff and fellows, and everybody who comforted, assisted, advised and supported my stay in Iceland, especial during the grieving time for my late sister, without you I would not made it to the end of the project.

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Finally, I would like to thank my husband and my daughters: Magano, Tukwatha, Tuna and Mbuka (my niece) for their courage and understanding during my absence from home.

TO GOD BE THE GLORY!

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LIST OF ABBREVIATIONS

a4a - Assessment for All Initiative

ADMB - Automatic Differentiation Model Builder

AIC - Akaike Information Criterion

ASPM - Age Structure Production Model

BIC - Bayesian Information Criterion

CPUE - Catch Per Unit Effort

FLR- The Fisheries Library in R

ICSEAF - International Commission for South-East Atlantic Fisheries

IVQ - Individual Vessel Qouta

GDP - Gross Domestic Production

GRT - Gross Rate Tonnage

GLM - Generalised Linear Model

GAM - General Additive Model

OPM - Operational Management Procedure

MFMR - Ministry of Fisheries and Marine Resources

MSE - Management Strategy Evaluation

NSA - Namibia Statistics Agency

RFMOs - Regional Fishery Management Organisations

RV - Research Vessel

TAC - Total Allowable Catch

APPENDIX

Table 1. Table of growth parameters

Year	Linf	K	t0	RSS(vbgf)	a	b	a50(both)	RSS(matage)	delta
2000	110.5	0.1	-1.7	6929	0.0	3.0	3.5	0.1	0.2
2001	104.5	0.1	-1.2	19029	0.0	3.1	2.7	0.2	1.6
2002	109.1	0.1	-1.3	1367	0.0	3.3	2.7	0.1	1.6
2003	104.5	0.1	-1.2	939	0.0	3.1	2.7	0.4	1.6
2004	104.5	0.1	-1.2	939	0.0	3.1	3.1	0.1	1.0
2005	107.8	0.1	0.1	1623	0.0	2.9	2.3	0.9	1.3
2006									
2007	110.0	0.1	-1.5	786	0.0	3.1	2.7	0.1	1.6
2008	111.3	0.1	-1.2	2342	0.0	2.8	3.1	0.1	0.9
2009	110.0	0.1	-1.3	2258	0.0	3.0	3.2	0.0	0.9
2010	103.1	0.1	-1.4	174571	0.0	3.1	3.5	0.0	1.5
2011	101.6	0.1	-1.4	24463	0.0	3.1	3.6	0.2	1.4
2012	110.0	0.1	-1.6	1872	0.0	3.1	3.6	0.0	1.5
2013	111.9	0.1	-1.2	813	0.0	3.1	3.5	0.1	1.2
2014	111.0	0.1	-1.2	34175	0.0	3.2	3.5	0.1	1.2
2015	111.0	0.1	-1.4	24940	0.0	3.0	2.7	0.2	1.5
2016	112.0	0.1	-0.8	12805	0.0	2.9	2.7	0.2	1.1

Table 2. Total monkfish landings per year

1974	**1975**	**1976**	**1977**	**1978**	**1979**	**1980**	**1981**	**1982**	**1983**	**1984**	**1985**
0.3	1.1	0.9	5.7	7.4	3.5	3.2	15.6	16.3	12.9	8.5	8.5
1986	**1987**	**1988**	**1989**	**1990**	**1991**	**1992**	**1993**	**1994**	**1995**	**1996**	**1997**
13	11.7	5	6.6	1.5	4.6	8.1	9.2	12.2	10.1	9.8	10.4
1998	**1999**	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
16.6	14.8	14.4	12.4	15.2	13.1	9	10.5	9.8	8.9	9.1	7.4
2010	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**					
9.1	7.2	12	10.8	11.3	11.5	11.5					

Table 3. The monkfish survey from all fleets and the survey coefficient

year	hake_surv	monk_surv	hake_cv	monk_cv	year	hake_surv	monk_surv	hake_cv	monk_cv
1974	0	0	0	0	1996	22	0	0.12	0
1975	0	0	0	0	1997	11	0	0.11	0
1976	0	0	0	0	1998	11	0	0.13	0
1977	0	0	0	0	1999	26	0	0.18	0
1978	0	0	0	0	2000	0	0	0	0
1979	0	0	0	0	2001	0	48	0	0.11
1980	0	0	0	0	2002	0	43	0	0.13
1981	0	0	0	0	2003	0	33	0	0.17
1982	0	0	0	0	2004	0	20	0	0.12
1983	0	0	0	0	2005	0	28	0	0.13
1984	0	0	0	0	2006	0	18	0	0.11
1985	0	0	0	0	2007	0	0	0	0
1986	0	0	0	0	2008	0	11	0	0.15
1987	0	0	0	0	2009	0	13	0	0.17
1988	0	0	0	0	2010	0	38	0	0.14
1989	0	0	0	0	2011	0	33	0	0.11
1990	0	0	0	0	2012	0	35	0	0.13
1991	0	0	0	0	2013	0	20	0	0.08
1992	0	0	0	0	2014	0	31	0	0.14
1993	0	0	0	0	2015	0	21	0	0.12
1994	35	0	0.13	0	2016	0	24	0	0.13
1995	0	0	0	0	2017	0	33	0	0.11

Table 4. Biomass per year and the CV (%)

Year	Biomass (No.) 3 Strata	CV (%)3 strata
2000	44 000 000	0.11
2001	52 000 000	0.16
2002	40 000 000	0.21
2003	27 000 000	0.21
2004	38 000 000	0.17
2005	25 000 000	0.15
2006		
2007	27 000 000	0.26
2008	22 000 000	0.17
2009	69 000 000	0.27
2010	43 000 000	0.2
2011	43 000 000	0.14
2012	25 000 000	0.12
2013	33 000 000	0.16
2014	18 000 000	0.11
2015	23 000 000	0.17

Table 5. Maturity probability of all ages per year and Selectivity

Year				Age						
	0	1	2	3	4	5	6	7	8	9+
2000	0.05	0.21	0.58	0.87	0.97	0.99	1.00	1.00	1.00	1.00
2002	0.03	0.10	0.31	0.64	0.88	0.97	0.99	1.00	1.00	1.00
2003	0.43	0.51	0.58	0.65	0.71	0.77	0.82	0.86	0.89	0.91
2004	0.03	0.08	0.24	0.51	0.78	0.93	0.98	0.99	1.00	1.00
2005	0.00	0.00	0.01	0.04	0.14	0.40	0.73	0.92	0.98	0.99
2007	0.04	0.08	0.16	0.28	0.46	0.64	0.79	0.89	0.94	0.97
2008	0.00	0.01	0.03	0.11	0.33	0.67	0.89	0.97	0.99	1.00
2009	0.02	0.05	0.12	0.26	0.48	0.71	0.86	0.94	0.98	0.99
2010	0.06	0.10	0.17	0.28	0.43	0.58	0.73	0.83	0.90	0.95
2011	0.03	0.07	0.19	0.41	0.67	0.85	0.95	0.98	0.99	1.00
2012	0.00	0.00	0.01	0.04	0.14	0.38	0.69	0.89	0.97	0.99
2013	0.02	0.04	0.10	0.19	0.35	0.56	0.74	0.87	0.94	0.97
2014	0.06	0.11	0.21	0.34	0.51	0.68	0.81	0.90	0.95	0.97
2015	0.00	0.00	0.01	0.16	0.82	0.99	1.00	1.00	1.00	
2016	0.01	0.03	0.15	0.45	0.80	0.95	0.99	1.00	1.00	1.00
Selectivity	0	0.5	1	1	1	1	1	1	1	1

Table 6. CPUE indices: CPUE indices (Table 7) based on bottom trawl fleets logbooks from 1991-2016. This is the total catches of monkfish from hake and monkfish fleets. Monkfish standardised CPUE by GLM.

Year	glm(cpue)	Year	glm(cpue)
1991	46.99801	2005	48.81118
1992	64.97658	2006	49.61433
1993	72.69396	2007	44.43237
1994	102.6394	2008	57.06522
1995	71.79977	2009	52.02144
1996	65.48551	2010	84.48702
1997	0	2011	89.81118
1998	173.9217	2012	132.9344
1999	166.018	2013	111.4686
2000	92.42751	2014	100.2798
2001	77.92744	2015	104.8861
2002	60.38776	2016	102.0513
2003	66.94979		
2004	36.75011		

Table 7: Growth parameters estimation by von Berttalanffy growth equation.

Biological parameters	***Lophius vomerinus***
Growth parameters (2000-2016):	
$L\infty$	*110*
K	*0.083*
t_0	*-0.98*
Length-weight relationship (2000-2016) (weight=aL^b)	*$W=0.012L^{3.069}$*
Length- at- 50 % Maturity (2000-2016)	*30.6cm*

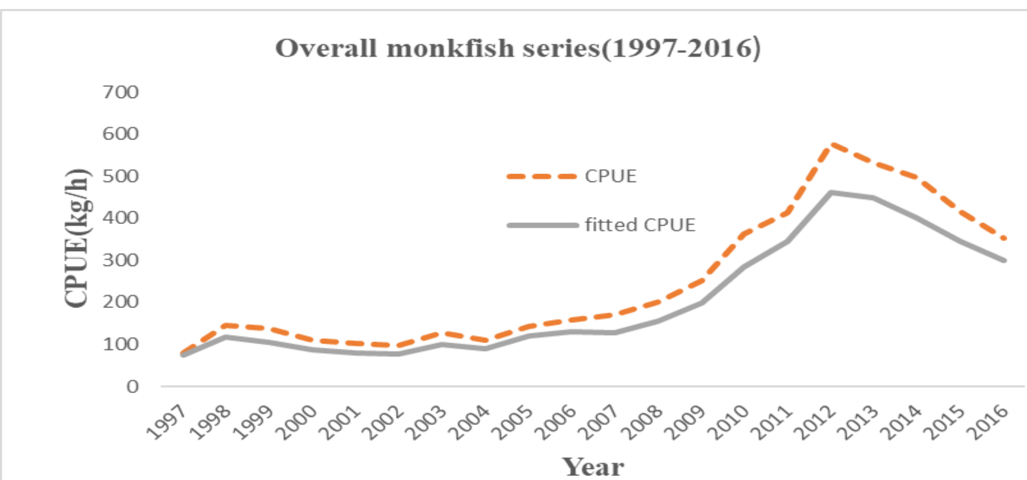

Figure 20: Index of abundance (CPUE in kg/h) for the Namibian monkfish obtained from fitting the GLM model from 1997 to 2016.

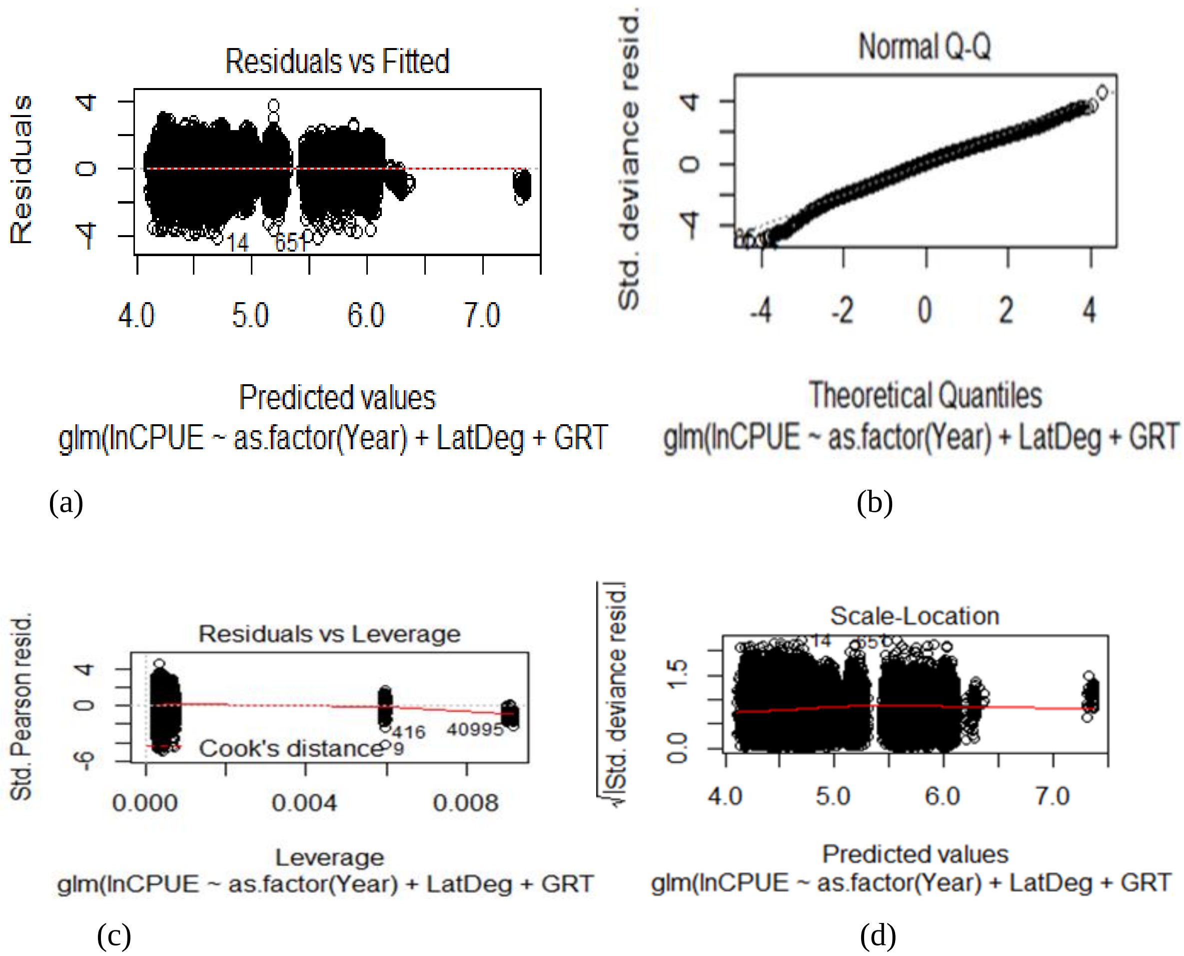

Figure 8: GLM Model diagnostics/Residual analysis:(a) a plot of the residuals, (b) plot for normality, (c) plot for constancy of the variance and (d) plot identifies residuals that are influential for monkfish data from 1997-2016.