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A fleet based surplus production model that accounts for increases in fishing power with application to two West African pelagic stocks

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ABSTRACT

Assessments of many West African fish stocks rely on fishery dependent catch and effort data. Typically, these treat the catch data as error free and some assume that fishing power does not change over time. To address these issues we develop a fleet based surplus production model that accounts for increases in fishing power. It allows errors both in effort and catch data so avoiding the assumption that catch data are exact. Mean annual fleet fishing power increase can be estimated when data from multiple fleets are available provided it can be specified for at least one fleet. The model is tested using simulated data and then applied to western stocks of anchovy (*Engraulis encrasicolus*) and bonga shad (*Ethmalosa fimbriata*) in the Fishery Committee for the Eastern Central Atlantic (CECAF) area. Both stocks appear to be over-exploited and near to collapse. Corrections for fishing power are important in the anchovy assessment and help to explain conflicting trends in the data. Uncertainty in the assessments is explored with a range of sensitivity tests.

1. Introduction

Many marine fisheries around the world are over-exploited (Worm et al., 2009; FAO, 2016). This problem threatens marine biodiversity and the well-being of > 260 million people who depend directly on marine fisheries for jobs, food and future opportunities (Teh and Sumaila, 2013). Throughout Africa, many coastal states draw much of their animal protein from fish (Belhabib et al., 2019) and the associated fisheries are important for employment (Belhabib et al., 2015). Fisheries in West Africa have undergone a long period of decline and major fishing nations such as Ghana have changed from being net exporters of fish to net importers (Atta-Mills et al., 2004). Nevertheless, these fisheries remain important and are a primary source of income for hundreds of coastal villages in Ghana (Dovlo et al., 2016), providing livelihoods for over two million people (Republic of Ghana, 2014). The mainstay of these fishing communities is the small pelagic fishery that includes sardine (*Sardinella* spp), anchovy (*Engraulis encrasicolus*), chub mackerel (*Scomber colias*) and bonga shad (*Ethmalosa fimbriata*). They are the most important small pelagic fish species throughout the Western Gulf of Guinea (Koranteng, 1993; Baldé et al., 2018) so that understanding the status of the stocks is essential for sustainable fisheries. A recent analysis of West African small pelagic stocks suggested these were generally over-exploited (Palomares et al., 2020) and while regular assessments of these stocks are undertaken by the Fishery Committee for the Eastern Central Atlantic (CECAF), many are uncertain. This may result from conflicting signals in the data, such as for anchovy, or simply that the model does not fit the data as is the case for bonga shad (FAO, 2019). In this paper we focus on anchovy and bonga shad, and develop a methodology to overcome a number of problems associated with these assessments.

The European anchovy is widespread and subject to fisheries from the Black Sea (Kideys, 1994), Mediterranean Sea (Pertierra and Lleonart, 1996), Bay of Biscay (Uriarte et al., 1996) as well as much of the West African coast to Angola and Namibia (FAO, 2019). It is typically associated with upwelling systems being found down to depths of 400 m (Schneider, 1990). In this region it is fished mainly by artisanal vessels using purse and beach seines, though tuna vessels may exploit it for bait (Amponsah et al., 2016). Bonga shad is found in shallow water down to 50 m often associated with estuaries (Schneider, 1990). It is fished using ring gillnets, purse seines, beach seines and surface driftnets (FAO, 2019). Additional information on the exploiting fleets is given in Supplementary Information. Unlike anchovy, bonga shad makes a small contribution to the overall catch of small pelagics in the region.

Typically, for artisanal fisheries that dominate in West Africa, the

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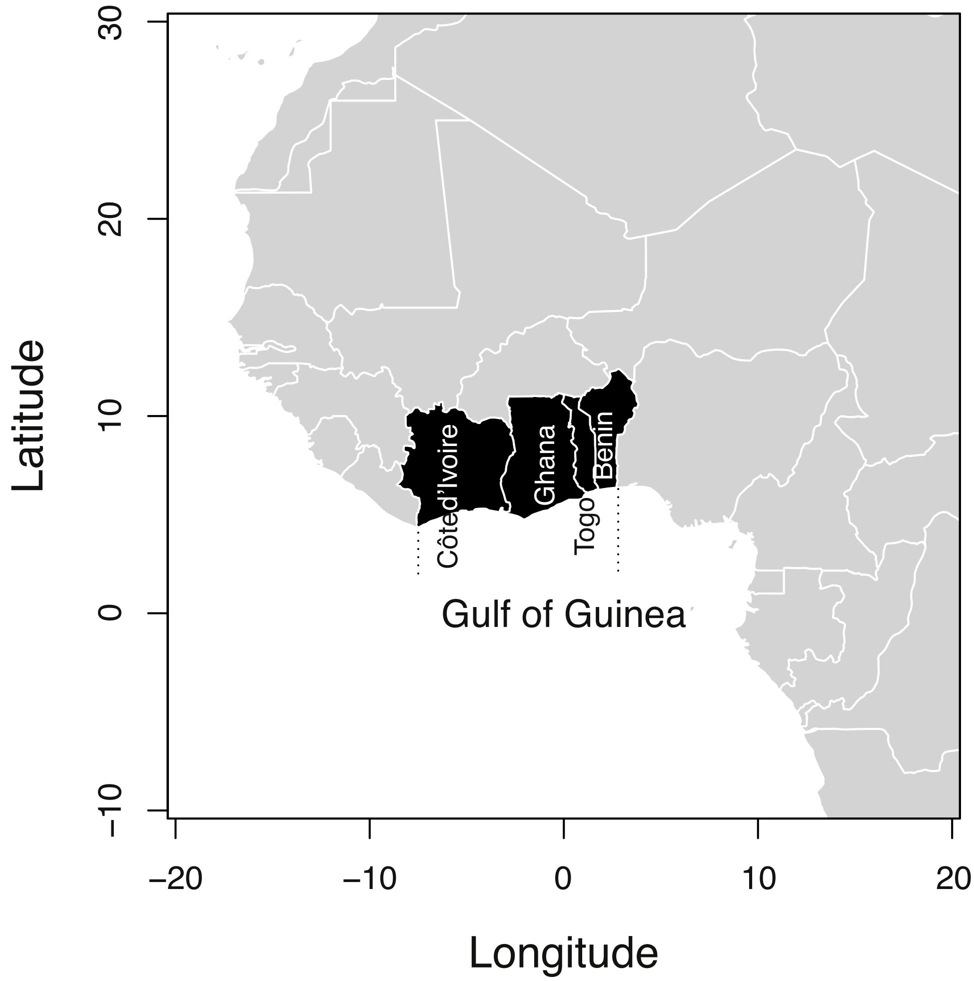

Fig. 1. Stock area considered for assessments corresponding to CECAF "western" zone shown as dotted lines. Assessments are based on catches and effort from Côte d'Ivoire, Ghana, Togo and Benin shown in black.

data available for stock assessments are a time series of total catch biomass and one or more series of catch per unit effort (CPUE) indices of abundance derived from effort data for different fleet segments (FAO, 2019). The CECAF assessment methodology uses a version of the Schaefer model (Schaefer, 1954; Haddon, 2011) fitted by least squares with one CPUE index and using aggregate catch data. Where multiple CPUE indices are available only one is selected for analysis, thus excluding potentially informative data. In addition, the catch data are also used to derive the CPUE index so that some information is used twice. Perhaps more importantly the catch data are treated as exact in the model but in reality are subject to measurement error because for most of these stocks the catch is estimated from sampling a subset of landing sites, rather than from a full census of landings. They are therefore subject to potentially large errors when raised to fishery level. In Ghana, for example, catches made by the artisanal fleet are estimated from a sample of 50 out of 300 landing sites (Bowen and Lazar, 2016). This fleet accounts for more than 80 % of the total catch of both anchovy and bonga shad in the CECAF western zone (FAO, 2019). Furthermore, effort data will also be subject to sampling error making a CPUE index prone to uncertainty. It would therefore be preferable to fit the model to catch and effort data separately with allowance made for different errors in each.

Since fishing vessels target the resource and are not designed to monitor its abundance, nominal fishing effort, such as the number of fishing trips, may be subject to bias if used as a metric of fishing activity (Bordalo-Machado, 2006). Such bias may be caused by the non-random sampling of the resource, but even if this is relatively minor, changes to effective fishing effort resulting from technological creep may be important. The temporal increase in fishing power, i.e. the ability of vessels to catch fish per unit time (Engelhard, 2008), if not accounted for, may result in under-estimation of effective effort and lead to inflated indices of abundance. Palomares and Pauly (2019) estimated that on average fishing power increased by 2–4 % per year due to technological innovation based on analysis of approximately 50 fleets worldwide. Where the time series of observed effort covers several years the impact of technological creep may be substantial and needs to be taken into account when calculating CPUE. While such a correction has been implemented for assessments of small pelagics in this region as part of a USAID project (Lazar et al., 2018) it is not usual practice in CECAF assessments.

A number of versions of the Schaefer model, such as ASPIC (Prager, 1994) that have been in use for some time, allow the inclusion of multiple CPUE indices facilitating the analysis of fleet data and avoid the need to select a preferred CPUE series. The development of state-space Schaefer models (Meyer and Millar, 1999; Punt, 2003) with stochastic population dynamics and more recently a continuous time version, (SPiCT, Pedersen and Berg, 2017) can now offer less restrictive, powerful tools for assessments. The methods do not explicitly estimate fishing power, however, and a correction would be required to the CPUE index before model fitting. The "CMSY" approach (Martell and Froese, 2013) avoids the problem of commercial effort data and associated changes in power by fitting the Schaefer model to catch data alone but at the expense of requiring prior assumptions about initial biomass depletion, resilience and MSY. Where multiple effort series are available it is therefore a less obvious choice for analysis.

The CECAF assessment of anchovy suggests the stock is under-exploited relative to MSY based on just one of the three available CPUE indices (FAO, 2019) despite a perception from other assessments that the stock is being over-exploited and is depleted (Lazar et al., 2018; EJF, 2020). Anchovy account for approximately 25 % of the total small pelagic catch (Lazar et al., 2018) so it is important to understand the state of this stock. For bonga shad, while there is a similar perception of decline, CECAF were unable to fit the Schaefer model to the available CPUE data. In order to examine these issues, we explore trends in CPUE and then develop a Schaefer model that makes use of the catch and effort by fleet so that estimates of fishing mortality can be partitioned out for management purposes. The model overcomes some of problems of analysing CPUE by allowing for errors in both the catch and nominal effort and can estimate the mean increase in fishing power for some fleets, hence potentially correcting for bias. The model is tested on simulated data and then applied to anchovy and bonga shad in the "western" zone of the southern CECAF area. In the absence of information on stock structure they are treated as unit stocks.

2. Materials and methods

2.1. Data

Data for the analysis were taken from the most recently available CECAF stock assessment report (FAO, 2019, Supplementary Information, Table S1) which provides estimates of catch and effort by fleet for a range of small pelagic species from 1990 to 2017. We analysed the "western" stocks of anchovy and bonga shad which covers catches by Ghana, Côte d' Ivoire, Togo and Benin (Fig. 1). Fishing effort is reported as days at sea or fishing days. For anchovy, effort series were available for the artisanal fleets of Ghana, Togo and Benin. For bonga shad, effort data were available for the artisanal fleets of Ghana and Benin. There were also data from the Côte d'Ivoire industrial fleet but the time series is short with the associated reported catches very small and intermittently recorded. They were therefore used in exploration of the raw CPUE but not in the final assessments.

Some acoustic survey data for anchovy are available from the FAO-Nansen programme (e.g. Krakstad et al., 2007). The data are intermittent beginning in 1999 and are not used in the CECAF assessments. We did, however, use the acoustic data in a sensitivity run of the assessment model.

2.2. CPUE model

Catch per unit effort is often treated as an index of relative stock abundance and this is the assumption made by CECAF (FAO, 2019) and USAID (Lazar et al., 2018) assessments. As an exploratory analysis we fitted a state-space model to the CPUE indices to extract any common abundance trend in the time series. The model draws on the approach suggested by Rosenberg et al. (1992), Zuur et al. (2003) and Conn (2010) for combining multiple indices of abundance. Here the CPUE for fleet k is assumed to be proportional to stock biomass at time t, B_t, and expressed on a log scale as:

$$\log\left(CPUE_{k,t}\right) = Q_k + \log(B_t) + \varepsilon_{k,t}\ , \quad \varepsilon_{k,t}\ \sim normal\left(0, \sigma_{cpue}\right) \tag{1}$$

Q is a fleet specific offset that scales the biomass to CPUE units, and $\varepsilon_{k,t}$ is a normally distributed random effect that represents the variation in the CPUE that is not explained by the trend in B. Successive biomass values are likely to be correlated and for simplicity we assume that they follow a random walk with a normally distributed process error, ε_t:

$$B_t = B_{t-1}\exp(\varepsilon_t), \quad \varepsilon_{k,t}\ \sim normal(0, \sigma_B) \tag{2}$$

For identifiability it is necessary to specify one of the Q parameters as there is no information in the CPUE data on the scale of the biomass. Setting Q = 0 for one fleet enables the estimation of the remaining Qs and means that the estimated biomass trend is scaled to the fleet with the specified Q. Provided our interest is in the change of biomass over time this limitation is not important.

We used the model to explore trends in the raw CPUE data without making any correction for changing fishing power or parametric assumptions about stock population dynamics. We fitted the model with the R package "rstan" (Stan Development Team, 2016), a Bayesian inference package that uses MCMC sampling to estimate posterior distributions of model parameters. We ran three chains of 50,000 iterations, a burn in period of 25,000, and a thinning rate of 100. All priors on the parameters were uniform.

2.3. Assessment model description

In common with assessments by CECAF (FAO, 2019) and USAID (Lazar et al., 2018) we use a Schaefer surplus production model derived from the familiar form due to Fletcher (1978) that expresses the population dynamics in terms of the carrying capacity, K, and maximum sustainable yield, m. The biomass, B, at time t is projected forward from the equation:

$$B_{t+1} = \left[\left(1 + \frac{4m}{K}\right)B_t - \frac{4mB_t^2}{K^2} - \sum_k Y_{k,t}\right]\exp(\varepsilon_t), \quad \varepsilon_{k,t}\ \sim normal(0, \sigma_B) \tag{3}$$

Where Y_k is the catch by fleet k and $\varepsilon_{k,t}$ is a random process error with a zero mean and standard deviation σ_B. The catch by fleet, $Y_{k,t}$, is a function of the biomass that depends on an annual fishing mortality, $F_{k,t}$, such that:

$$Y_{k,t} = B_t F_{k,t} \tag{4}$$

It might be supposed that F is approximately proportional to fishing effort, f, with catchability, q, so that F = qf. This is equivalent to the widely used assumption that CPUE is proportional to the biomass (see Supplementary Information). However, if effective fishing effort increases over time due technological creep by an annual power increment δ, then f (or q) must be inflated by an amount $(1 + \delta)^{(t-1)}$ so that:

$$F_{k,t} = q_k f_{k,t}(1 + \delta_k)^{(t-1)} \tag{5}$$

The effect of δ in Eq. (5) can be considered either as correction to effective effort (such as days fishing) or a correction to catchability since the expression is multiplicative.

Note that the total fishing mortality, $F = \Sigma F_{k,t}$ can be greater that one since it is in effect a yield biomass ratio Y/B. Here the yield is the total catch over the year while, B, is the biomass at the start of the year. If F > 1 it implies that in-year production makes a substantial contribution to the total catch, over and above the biomass at the start of the year.

In order to reduce the number of effective parameters to be estimated we assume that fishing effort for each fleet follows a separate random walk with standard deviation, σ_f;

$$f_t \sim lognormal\left(\log(f_{t-1}), \sigma_f\right) \tag{6}$$

Here, for simplicity, the same process error standard deviation is applied to all fleets to limit the number of parameters to be estimated. It is possible, however, that the variability in each fleet may differ in reality.

The q parameters are not identifiable unless at least one is specified. Provided fishing mortality in the years immediately prior to year 1 does not change radically, the initial biomass, B_1, may be considered to be close to equilibrium and one of the catchability constants, q, can then be expressed in terms of other model parameters. Writing $B_1 = dK$, where d is the depletion from virgin biomass (K), then q for fleet 1 is given by:

Table 1
Model parameters and their description. Where applicable, priors used in the base models for anchovy and bonga shad are shown. For K, the limits a and b are defined as a=√(minimum observed catch), b=√(10*maximum catch).

Parameter	Description	Prior
m	Maximum sustainable yield (MSY)	Uniform(0.001, 2*maximum catch)
K	Carrying capacity or virgin biomass	Uniform(a,b) on square root scale
d	Depletion - initial biomass as a proportion of virgin biomass	Uniform (0,1)
q_k	Catchability coefficient for fleet k	Uniform(0.001,100)
δ_k	Mean annual fishing power increment for fleet k	Uniform(−0.05,0.1)
σ_f	Standard deviation of fishing effort process error for all fleets	Uniform(0,1)
σ_B	Standard deviation of biomass process error	Uniform(0,1)
κ_k	Dispersion parameter for negative binomial distribution of catch observation errors	Uniform(0.0001,100)
σ_k	Standard deviation of observation errors on fishing effort	Uniform(0,10)
B_t	Biomass in year t	NA
$Y_{k,t}$	Catch (yield) by fleet k in year t	NA
$Y'_{k,t}$	Observed catch by fleet k in year t	NA
$F_{k,t}$	Fishing mortality by fleet k in year t	NA
$f_{k,t}$	Nominal fishing effort by fleet k in year t	NA
$f'_{k,t}$	Observed nominal fishing effort by fleet k in year t	NA

$$q_1 = \frac{\left(\frac{4m}{K}(1-d) - \sum_{2}^{n} q_k f_{k,1}\right)}{f_{1,1}} \tag{6}$$

With this constraint, it is possible to estimate the remaining q values. Clearly the catches, Y, and effort, f, are observed with error. For fishing effort, we assume lognormal errors so that observed effort f ', is given by:

$$f'_{k,t} \sim lognormal(f_{k,t},\ \sigma_k) \tag{7}$$

The catches for the stocks of interest here are derived from surveying a sample of landings which is then scaled to fleet level. The associated observation errors may therefore be large. It is commonplace to assume lognormal errors (e.g. Nielsen and Berg, 2014) and this might be used but since there are zeros in some of the catch data, we assume that the observed catch, Y', is subject to negative binomial errors with dispersion parameter, κ, (Cook, 2019):

$$Y'_{k,t} \sim negative\ binomial(Y_{k,t},\ \kappa_k) \tag{8}$$

We also ran the model with a lognormal error assumption as a sensitivity test but with zero values treated as missing. Table 1 lists model parameters and their description.

2.4. Assessment model parameter estimation

Parameters were estimated by fitting the model to the catch and effort data using the same r package "rstan" (Stan Development Team, 2016) as for the CPUE model. Each simulation consisted of 100,000 iterations using three chains, a burn in of 50,000, and thinning rate of 100. Chain mixing was checked to ensure the Rhat = 1. In the "reference model" uniform priors were assumed for all parameters and should give similar results to maximum likelihood. However, it is often the case that there is insufficient information in the data to estimate both m and K adequately, especially if the population shows only a declining trend (Hilborn and Walters, 1992). We therefore investigated alternative weakly informative priors for K that included uniform distributions on either a log or square root scale. The value of δ was fixed for one reference fleet, the Ghanaian artisanal fleet, with the remaining δ values estimated in the model.

Table 2
Model configurations used in the anchovy and bonga shad assessments. Model base_lnorm uses a lognormal distribution for the catch observation errors instead of the default negative binomial used in all other models.

Stock	Model	Ghana artisanal, δ	Togo artisanal, δ	Benin artisanal, δ	Acoustic survey included
Anchovy	base	0.015	estimated	estimated	No
	base_lnorm	0.015	estimated	estimated	No
	base_δ[1] = 0.03	0.03	estimated	estimated	No
	Ghana_only	0.03	NA	NA	No
	Togo _only	NA	0.03	NA	No
	Benin _only	NA	NA	0.03	No
	δ_all = 0	0	0	0	No
	base + acoustic	0.015	estimated	estimated	Yes
Bonga shad	base	0.015	NA	estimated	NA
	base_lnorm	0.015	NA	estimated	NA
	base_δ[1] = 0.03	0.03	NA	estimated	NA
	Ghana_only	0.03	NA	NA	NA
	Benin _only	NA	NA	0.03	NA
	δ_all = 0	0	NA	0	NA

2.5. Simulation testing

The model was tested using simulated data to check performance and whether the power increment, δ, was estimable. The simulated data were based on an initial model fit to the anchovy data using the reference model. In this fit, δ for the Ghana artisanal fleet was fixed at 0.03 as it is the mid-point of the range for technological creep given by Palomares and Pauly (2019). Estimates of δ for the remaining fleets are therefore conditioned on this assumption.

Simulated data were derived from values of K = 210000, m = 70,000 and δ = 0.03, 0.07 and 0.05 respectively for three fleets. The process error on biomass was set at $\sigma_B = 0.2$. A continuous increase in fishing mortality was assumed for each fleet. The increase in total fishing mortality is likely to be representative of the stocks involved given the tendency for effort in the Ghanaian artisanal fleet, which takes over 80 % of the catch, to increase over time (FAO, 2019). Values of F by fleet used to derive simulated data are given in Supplementary Information (Table S2) along with the error distributions applied (Table S3). A total of 50 sample biomass trajectories and catches were generated using Eqs. (3) and (4). Fishing effort, uncorrected for fishing power, was derived from the true fishing mortality by solving Eq. (5) for f given values of δ and assuming q = 1 for all fleets. For each of the 50 biomass trajectories errors were added to the derived catches and effort to create pseudo observations.

In the initial fit of the model to anchovy data from the reference model (uniform priors on m and K), the posterior distribution for K had a very long right hand tail with an indistinct mode. Using the simulated data, we investigated other priors on K to identify weakly informative prior distributions that did not excessively bias the estimates. These were uniform distributions on a log scale or square root scale that give higher probability to lower values. The square root scale is intermediate between raw uniform and the log scale uniform. The model was also run with alternative assumptions on the power increment, δ to test sensitivity to mis-specification. These included fixing δ = 0.03 or 0 for all fleets and assuming $\delta_1 = 0.015$ for the conditioning reference fleet. The models were fitted to the 50 data sets and the median value of the estimated values for m, K, B, F and δ saved. We also estimated median values of B/B_{MSY} and F/F_{MSY} for each data set as potentially more robust quantities measuring relative change.

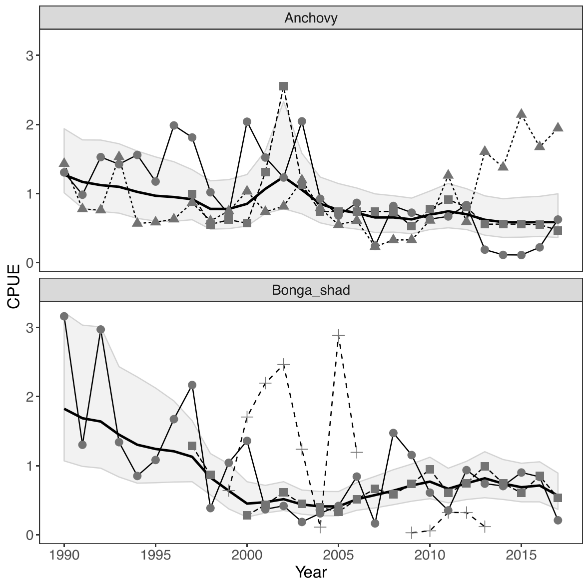

Fig. 2. CPUE model results for anchovy and bonga shad. The solid line shows the fitted common biomass trend with 95 % CI indicated in grey. The raw CPUE data are shown after rescaling each series to Ghana artisanal units using the estimated catchability, Q. ● Ghana artisanal, ▲ Togo artisanal, ■ Benin artisanal, + Côte d'Ivoire industrial.

2.6. Anchovy and bonga shad assessments

For the real data we used the model with a square root uniform prior on K based on results from simulation tests. All priors used are shown in Table 1. We fixed δ = 0.015 for the Ghana artisanal fleet, a value consistent with estimates given by Lazar et al. (2018), while estimating δ for the remaining fleets. This is referred as the "base model" and was used for both anchovy and bonga shad. We included a sensitivity run with δ = 0.03 to reflect the typical value estimated by Palomares and Pauly (2019). In the case of anchovy, inspection of the CPUE data for Ghana and Togo shows conflicting trends in recent years (FAO, 2019). Hence as sensitivity runs, the model was fitted separately to the Ghana, Togo and Benin effort series with δ fixed at 0.03 in each case. For bonga shad the model was also fitted to the Ghana and Benin effort data separately as sensitivity tests. In addition, we ran the base model assuming lognormal errors in the catch data instead of negative binomial errors, but treating zeros as missing data. The model configurations are summarised in Table 2 and include a run with the base model using acoustic data for anchovy. For this run the acoustic survey was treated as a relative index proportional to the true biomass with lognormal observation error.

3. Results

3.1. CPUE model

The combined CPUE trends for anchovy and bonga shad both show a long term decline (Fig. 2), although in bonga shad there has been some increase in CPUE in the latter part of the time period. For anchovy, the

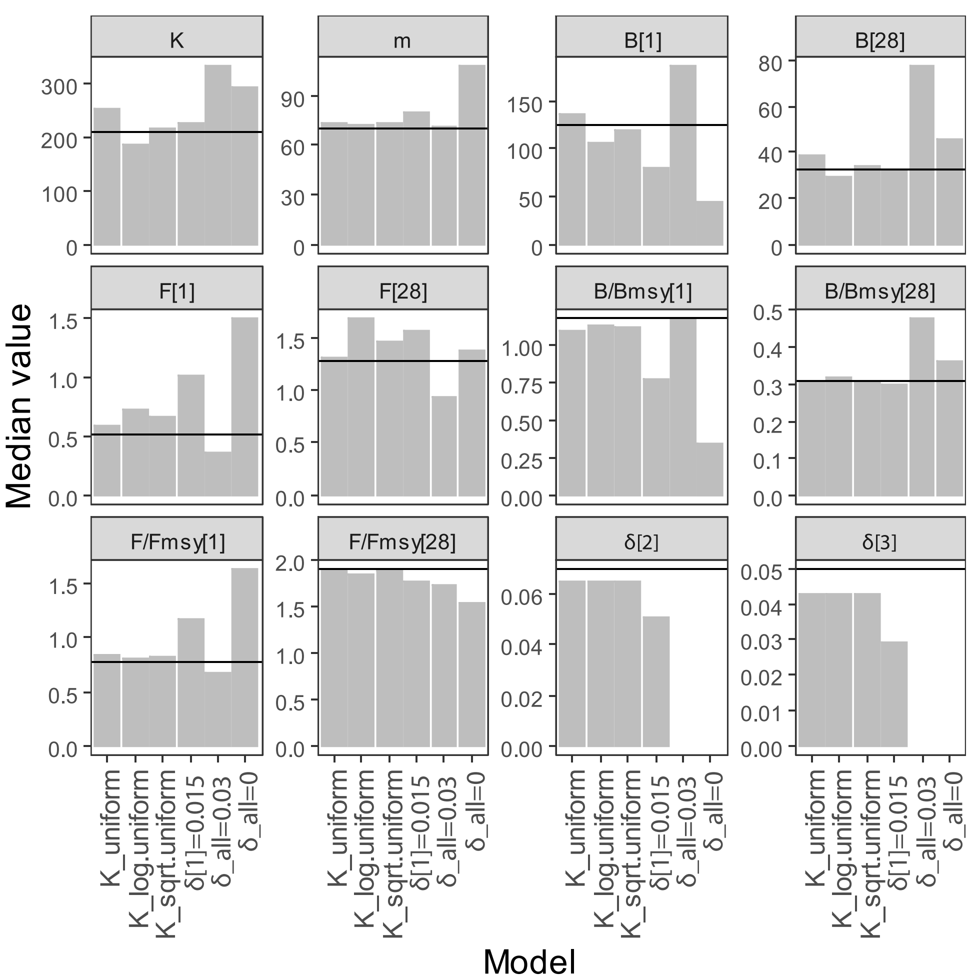

Fig. 3. Sensitivity runs on simulated data. The bars show the mean median value of 50 simulations. The solid horizontal line shows the true value. The model configurations labelled K refer to the prior distribution on K. The K_uniform run is the reference model. Models labelled δ refer to the assumption made for fishing power. When δ = 0 for all fleets, no correction is made for fishing power. Numbers in square brackets for F and B refer to the first and last year. For δ the brackets refer to the fleet.

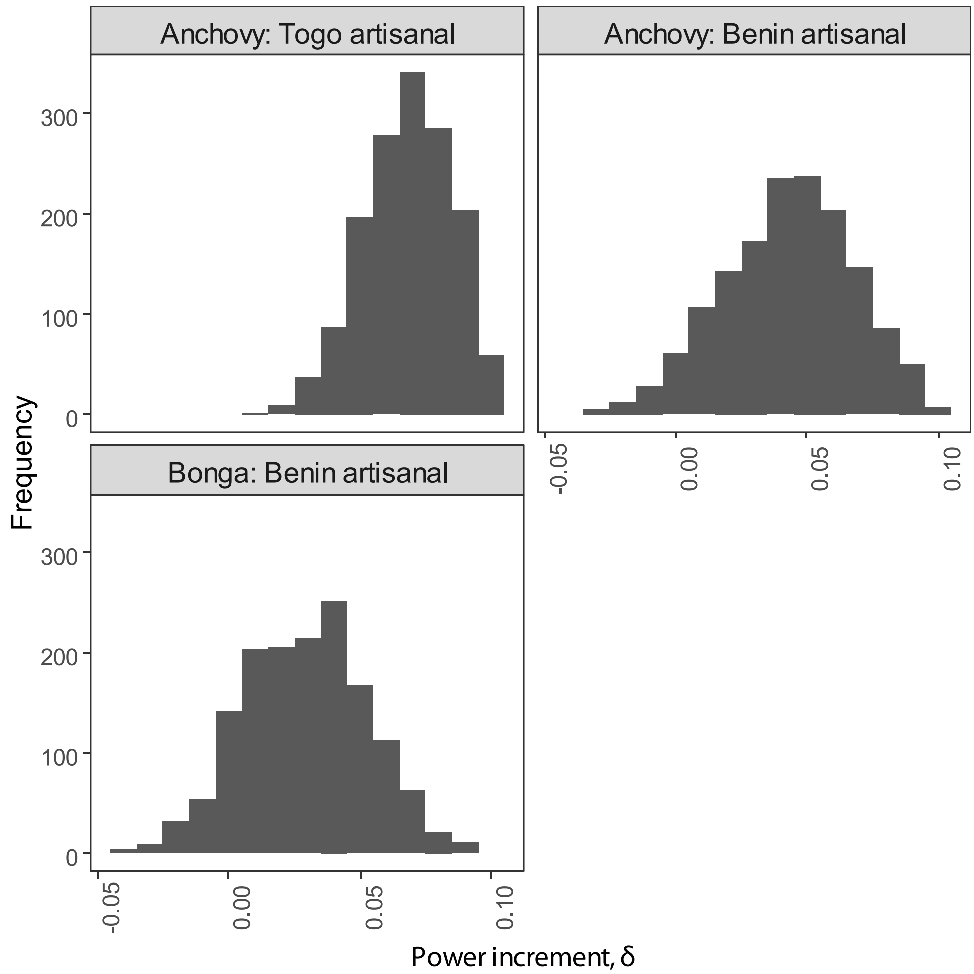

Fig. 4. Posterior distributions for the fishing power parameter, δ, from the assessments of anchovy and bonga shad using the base model. The value of δ for the Ghana artisanal fleet was fixed at 0.015.

Togo artisanal fleet CPUE, used in the CECAF assessment, stands out as showing a strong recent increase unlike the other two fleets that indicate a decline.

The CPUE for bonga shad in the Ghana and Benin fleets show fairly good agreement but with much more annual variability in the Ghana CPUE. The Cote d'Ivoire CPUE is very incomplete and appears highly variable with no consistent signal. The combined trend is therefore determined by the Ghana and Benin fleets.

3.2. Assessment model simulations

Estimates for the main parameters and other quantities of interest for the different model runs using simulated data are summarised in Fig. 3. The values of fishing power change, δ, for the two simulated fleets are fairly well estimated for all models but with some negative bias. For the reference model the estimates of K and m show positive bias, especially for carrying capacity. Of the alternative priors on K, the square root uniform performed best in reducing bias on these parameters but with some increased positive bias on fishing mortality. However, there is very little bias in the F ratio. Mis-specification of δ either for the reference fleet or if fixed over all fleets caused substantial bias in the estimates of B and F in the first year, but in the final year this was much lower except when $\delta = 0.03$ for all fleets. In all cases the F ratio in the final year was subject to low bias, suggesting that perception of exploitation status in the final year is fairly robust. Two sensitivity runs that fixed the power increment too low, at zero for all fleets or $\delta_1 = 0.015$, tended to give an overly pessimistic perception of the stock status in the initial year but approached the correct value in the final year. The model correctly recovered the true trends in biomass and fishing mortality both on the absolute and relative scales but with a small amount of bias evident in the biomass estimates (Fig. S1, Supplementary Information).

3.3. Anchovy and bonga shad assessments

Posterior distributions of the principal model parameters are given in Figs. S3 and S4 in Supplementary Information and show distinct modes. In both the anchovy and bonga shad base models the posterior distributions for δ showed a clear mode above 0 (Fig. 4) implying increasing fishing power over time and this is important in the determination of stock status. The effect is clearly seen in the fit to the catches for the Ghana and Togo artisanal fleets for anchovy with and without correction for technological creep (Fig. 5). The main effect of estimating the correction is to fit the Ghana catch series more closely. For the Togo fleet, the estimated value of δ is 0.07 indicating a substantial increase in effective effort compared to the effective effort for the Ghanaian fleet where $\delta = 0.015$. The high value of δ for Togo enables the model to reconcile the otherwise conflicting trends in the data. Estimating the fishing power parameters reduced the Deviance Information Criterion (DIC) from 1484 to 1471.

While the median value of δ estimated for the Benin fleet is large (0.03) in the bonga shad assessment, the effect of increasing fishing power is less substantial and the correction makes little difference to the fit to the data (Fig. 6). There is no improvement in the DIC when estimating δ which increases from 607 when it is fixed at zero, to 609 in the

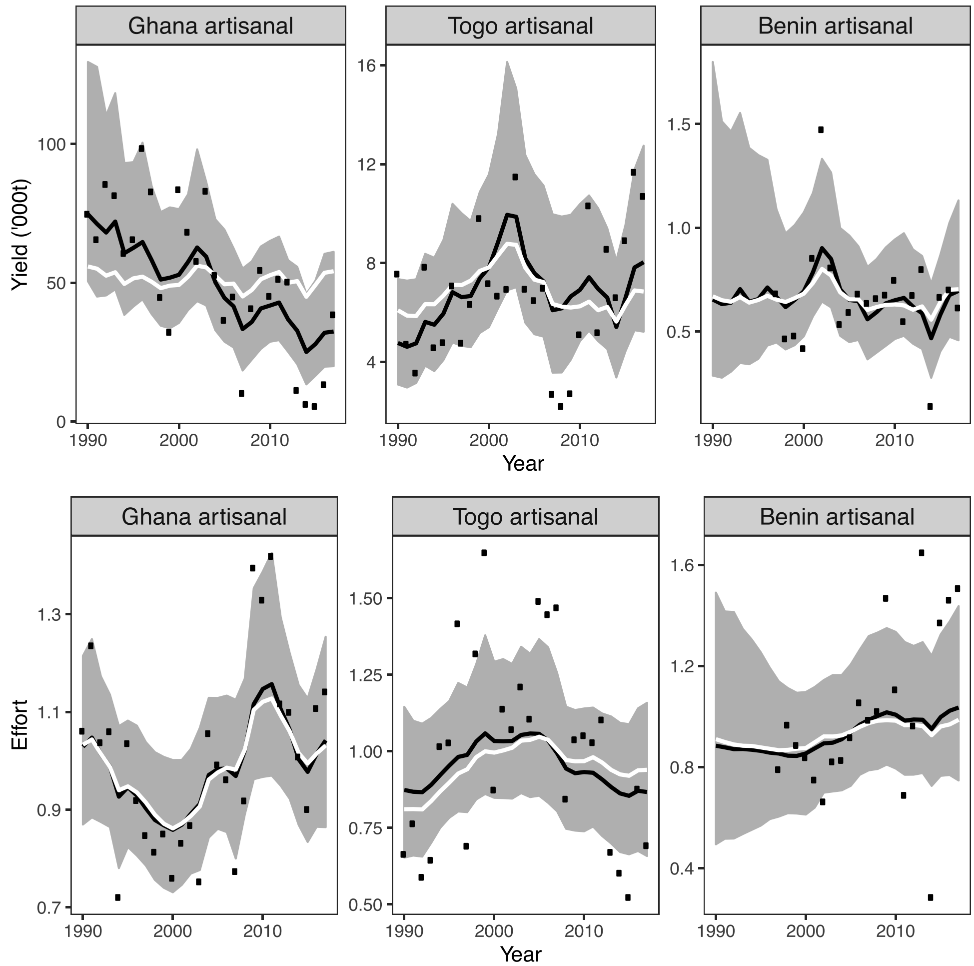

Fig. 5. Anchovy. Model fit to the catch and effort data by fleet. The solid black line shows the median value from the base model and the shaded area the 95 % CI. The white line shows the median value from the model when no correction for fishing power is made (δ = 0 for all fleets).

base model. For both the anchovy and bonga shad assessments, the posterior distributions of δ for the Benin artisanal fleet are similar (Fig. 4).

The long term trends in relative biomass show a decline for both stocks (Fig. 7). These trends are very similar to those emerging from the CPUE model but the decline is more pronounced in the assessment model results as would be expected given the correction for fishing power change. While the uncertainty in the estimates is very large, in both stocks the upper bound for B/B_{MSY} in the most recent year is less than 1 indicating the current biomass is below B_{MSY}.

The estimated biomass and observed yield in relation to the expected equilibrium values from the base model for both stocks is shown in Fig. 8. Here the solid lines show the estimated equilibrium value when fishing continuously for any value of F. The plotted points show how far the stock was from the equilibrium and where the stock would be expected to be if fishing continues at the 2017 rate. Fishing mortality increased more or less continuously leading to long term decline in biomass and yield. The current fishing mortality was well above F_{MSY} with $F(2017)/F_{MSY}$ for anchovy at 1.99 ± 0.76 and for bonga shad at 2.20 ± 0.86 (Figs. 9 and 10, base model). Fishing mortality in 2017 for both stocks is in the region where the estimated equilibrium biomass is zero and implies a high probability of stock collapse.

The results of sensitivity analysis for anchovy are shown in Fig. 9. The run with the Togo fleet alone stands out as giving a different perception of stock status compared to all other models. Here F is around 50 % of F_{MSY} and stock is approximately 50 % above B_{MSY}, a result which is similar to the CECAF assessment (FAO, 2019) that uses the same data. This contrasts most with the model using only Ghana data which points to a heavily over-exploited stock with F in 2017 2.5 times F_{MSY} and the associated biomass only 25 % of B_{MSY}. For the other models, while there were clear differences in the estimated quantities, all suggest the stock is fished above F_{MSY} with the biomass below B_{MSY}.

Results from the lognormal error assumption for the catch data (base_lnorm, Fig. 9) are very similar to the base model. Including the acoustic survey data made almost no difference to the perception of stock status. These data were effectively down-weighted by the model and have little influence on the estimates of stock biomass (Supplementary Information Fig. S2). The proportionality constant (q) of this survey was estimated to be only 0.36 implying it does not cover the whole stock. The model where no correction is made for increasing fishing power was closest to the model using Togo data alone. This is because without correcting for fishing power the model fits the Togo catch data but is unable to fit the Ghana catches, effectively giving them low weight. These sensitivities point to the difference between the Ghanaian and Togo data that individually imply conflicting stock status.

The bonga shad data do not display the same conflicting trends seen for anchovy as can be seen from the sensitivity results in Fig. 10. Here all models estimate the stock to be over-exploited with the F ratio above and the biomass ratio below 1. The estimates of K and F_{MSY} are very variable. They are clearly sensitive to the value of δ set for the reference fleet but this does not change perceived stock status. However, where there was no correction for fishing power the perception of stock status was the most optimistic, as might be expected. The lognormal error assumption on the catches (base_lnorm, Fig. 10) made very little

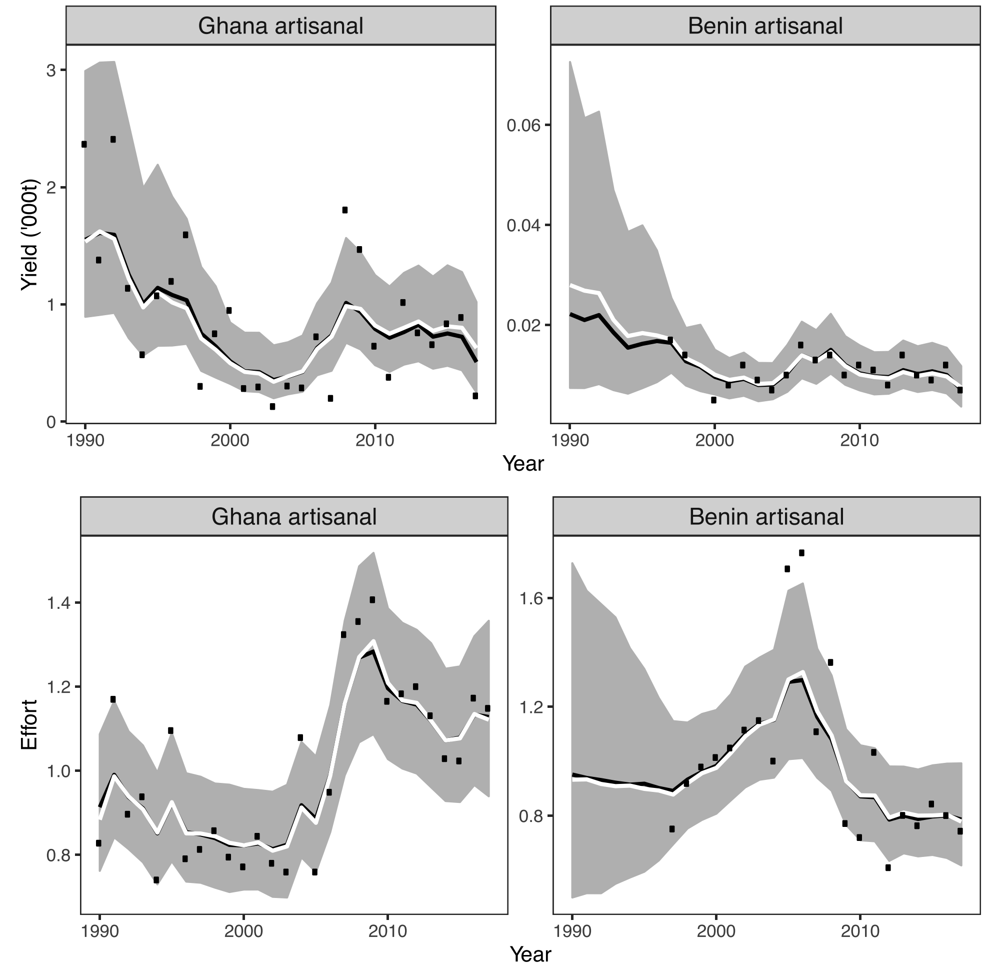

Fig. 6. Bonga shad. Model fit to the catch and effort data by fleet. The solid black line shows the median value from the base model and the shaded area the 95 % CI. The white line shows the median value from the model when no correction for fishing power is made (δ = 0 for all fleets). The black and white lines are coincident for much of the time series.

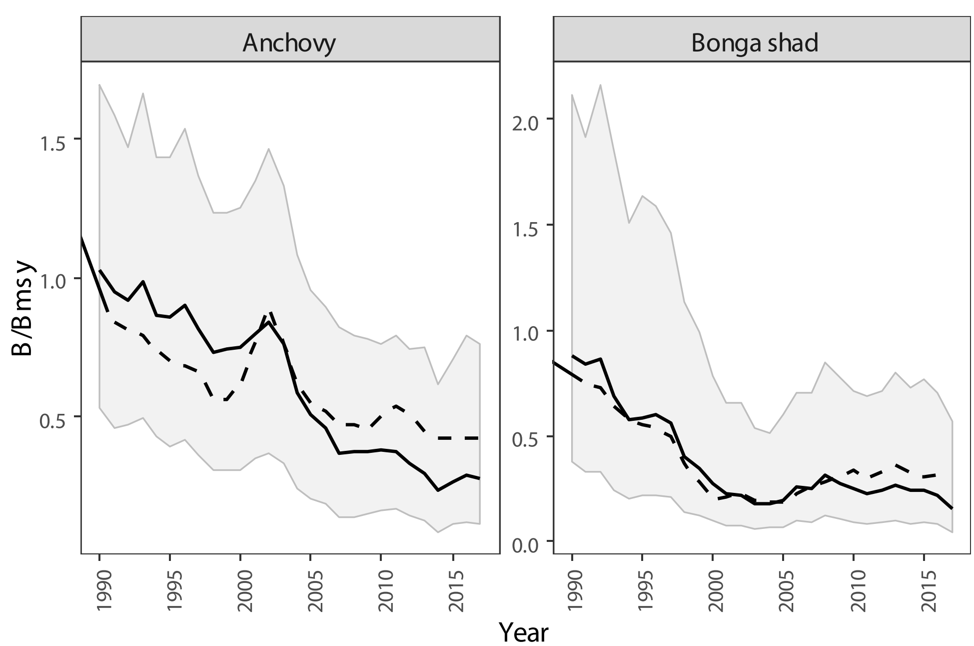

Fig. 7. The median biomass ratio (B/BMSY) for anchovy and bonga shad shown as a solid line with the 95 % CI indicated in grey. The dashed line shows the estimated trend from the CPUE model (Fig. 2) rescaled to the mean of the biomass ratio.

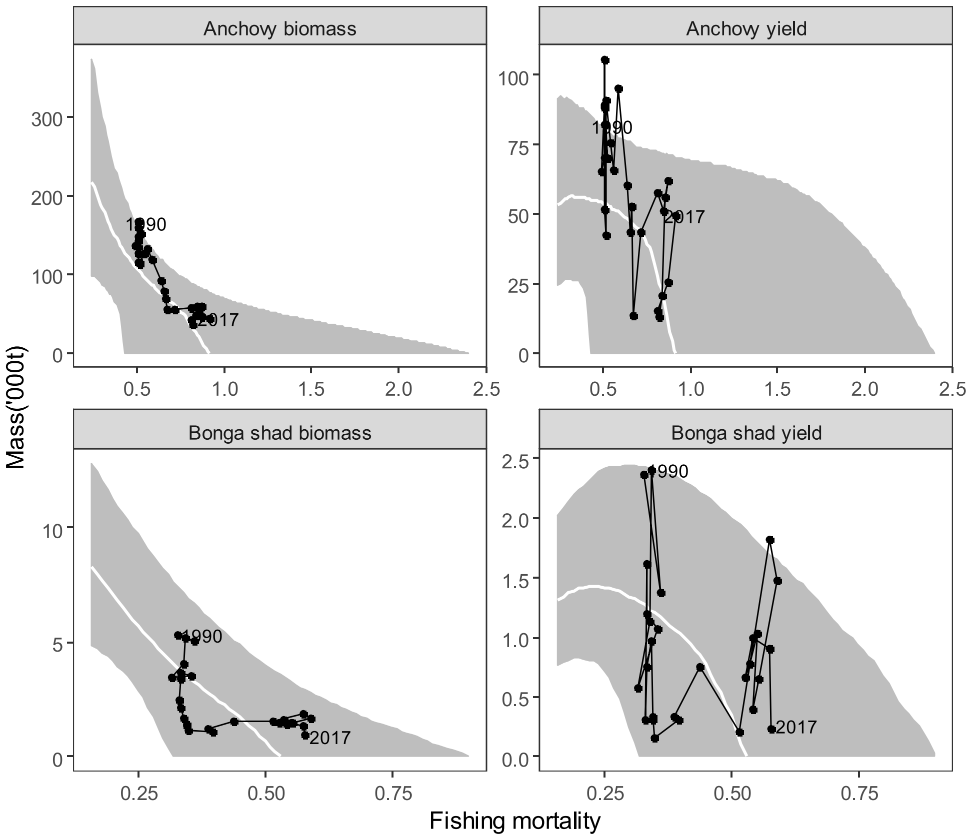

Fig. 8. Equilibrium biomass (left) and yield (right) estimated for anchovy (top) and bonga shad (bottom) from the base model (solid white line). The lines are the median values from the simulated posterior distribution samples and may differ slightly from the straight line (for biomass) and parabola (for yield) expected from a deterministic calculation due to the shape of the distribution. Shaded area corresponds to the 90 % CI. The time series of biomass estimated from the model and observed catch (yield) is over-plotted as points joined by a black line. The start year and end year of the time series are indicated. Both stocks are being fished above F_{MSY} (right) and are close the point of full stock collapse (left).

difference to the estimates.

The interval estimates for the parameters and other quantities of interest shown in Figs. 9 and 10 are large illustrating the range of uncertainty. The intervals are especially large for estimates of carrying capacity K. The ratio estimators of stock status (F/F_{MSY} and B/B_{MSY} in 2017) relative to MSY, while large in some cases, still categorise the stocks as over-exploited/depleted with the exception of anchovy using Togo data only or not correcting for fishing power. Here, even though the point estimates suggest the stock is not depleted or over-exploited, the interval estimates include alternative interpretations of status.

4. Discussion

The use of fishery dependent data to derive indices of abundance may result in bias caused by the non-random sampling of the resource, but even if this is relatively minor, changes to effective fishing effort resulting from technological creep or other causes may be important. Measuring the increase in fishing power is difficult since it is the result of a range of factors such as vessel size, engine power, on board handling and gear design, as well as access to navigation technology, behavioural changes by vessels and local political considerations. In the model described here, it appears possible to estimate the combined effect of these factors on the increase in effective effort for some fleets within the assessment. These estimates are conditioned on having a good estimate of the change in fishing power of at least one reference fleet. Given such an estimate, the results of simulations show that fleet specific estimates of the mean annual increase in fishing power may be made.

Previous assessments of anchovy have given a mixed picture of stock status. The CECAF assessment estimated the stock to be fished below F_{MSY} and the biomass above B_{MSY} with a similar conclusion reached for the southern stock of anchovy off Congo (FAO, 2019). An assessment using length frequency data collected over a period of 6 months estimated the western stock to be over-exploited (Amponsah et al., 2016). A more recent assessment of combined small pelagic species that included anchovy concluded the stock was over-exploited (Lazar et al., 2018). This analysis used a similar surplus production model to the one described here but included only a single CPUE index derived from Ghanaian catch and effort data. The latter was, however, corrected for fishing power. Since the assessment combined a number of species including *Sardinella* spp. and chub mackerel (*Scomber colias)* it is not possible to draw specific conclusions about anchovy stock status alone.

In common with Lazar et al. (2018), results from our analysis estimate an over-exploited stock when using Ghanaian CPUE data alone. However, questions arise over the interpretation of conflicting signals in the Togo data which were chosen as the basis for the assessment undertaken by CECAF. The reasons for CECAF reliance on Togo data are unclear, but they give a contrasting perception of stock status, just as they do in our analysis, even when applying a conventional value ($\delta = 0.03$) to correct for fishing power. Estimating the power correction for the Togo effort, which appears to be large, overcomes this problem when all three available fleets are used in our assessment, and suggests the over-exploited status is more likely.

Anchovy populations are well known to be heavily influenced by environmental conditions and may be associated with regimes that shift between favouring either anchovy or sardine (Lluch-Belda et al., 1989; Perry and Sumaila, 2007). As the sardine populations in the same region of West Africa are estimated to be low (FAO, 2019; Lazar et al., 2018), there may be some reason to believe that the recent conditions favour anchovy. However, since both the Ghanaian and Benin data when used separately in the assessment indicate an over-exploited stock, the evidence tends to support a pessimistic view of the stock. It could be argued that environmental variability such as the strength of upwelling may violate the assumption in the Schaefer model of constant m and K. While this may occur, the CPUE model that makes no specific parametric assumptions about population dynamics (such as constant m or k) shows very similar trends in relative biomass for both anchovy and bonga shad.

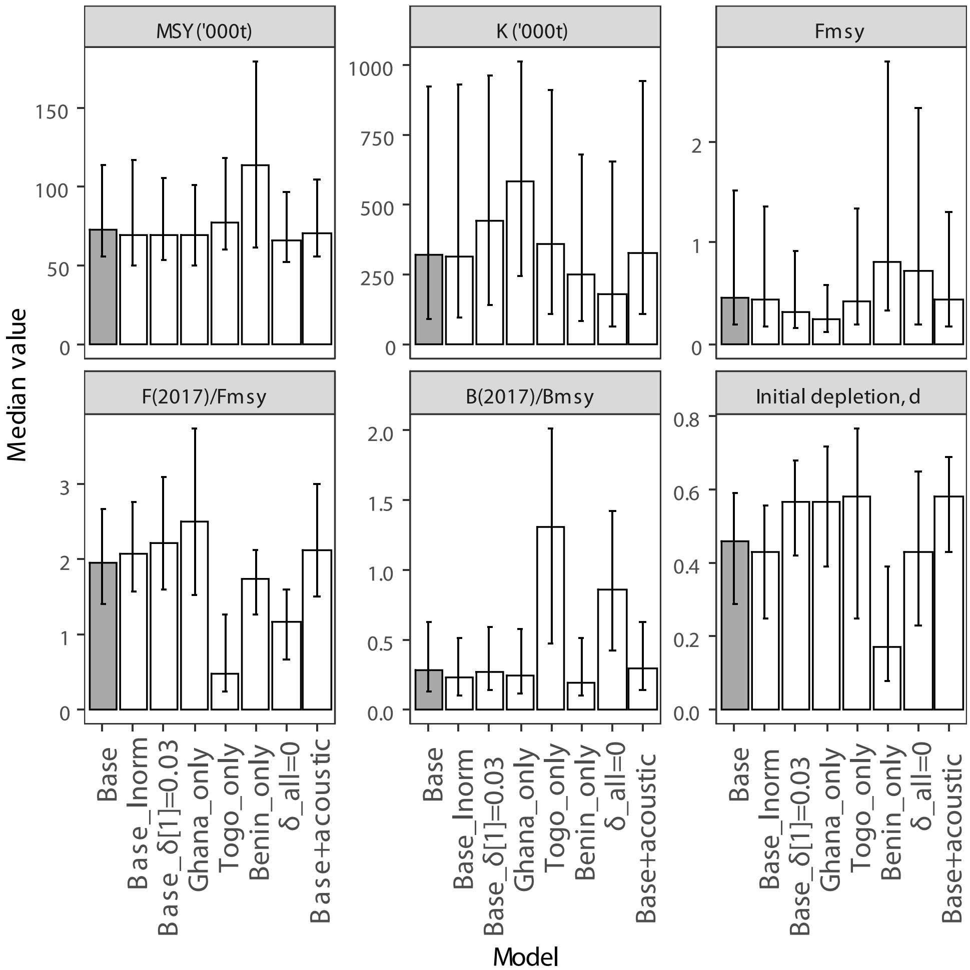

Fig. 9. Anchovy. Sensitivity results of key parameters and quantities of interest. Bars show the median parameter value. The base model is shown in grey and sensitivity runs in white. Error bars show the 90 % credible intervals. Model definitions are given in Table 1.

The model results therefore appear to be robust to the constancy assumption in this case.

Both in 2009 and 2018 CECAF were unable to obtain a satisfactory assessment for the western stock of bonga shad when fitting a Schaefer model using a single CPUE series (FAO, 2009; 2019). For the adjacent stock to the south they estimated the stock to be fished below F_{MSY} and the biomass above B_{MSY}. Similar results were reported for both the northern and southern stocks in this region in 2009 (FAO, 2009). In contrast the stock off Senegal was estimated to be over-exploited (Baldé et al., 2018) with a declining trend in biomass. The Senegal assessment was based on an age based virtual population analysis (Pope, 1972) after converting length to age using growth parameters. The assessment may not be reliable as no abundance index was used to "tune" the analysis. Hence the status of the stocks is not clear from earlier studies.

Our results indicate that application of a fleet based model with correction for fishing power can obtain a satisfactory fit to the available data for the western stock of bonga shad. The model therefore offers a potential solution to assess the stock for management purposes. Unlike the CECAF assessments of the northern and southern stocks, the western stock appears to be severely over-exploited and may be close to collapse. This result is insensitive to assumptions about fishing power or choice of data series included in the analysis. The biomass decline also emerges from analysis of the raw CPUE data.

The ability to fit the bonga shad data probably arises from treating the catch data as subject to error and modelling the biomass with process error. For the stocks considered here catches are estimated from surveys of landing sites and are therefore more prone to measurement error than when catches are derived directly from a full census of landings. In addition, there are uncertainties arising from the format for reporting of catches and this may introduce other biases. Nunoo et al. (2014) reconstructed catches for Ghana, the country accounting for most of the catch in these stocks, but did not find a large discrepancy in the reconstructed catches compared to those reported to FAO for the artisanal fleet. Nevertheless, catches from subsistence fishing may be absent leading to bias. Provided such bias remains similar over the period of the assessment, it will mainly affect the absolute scale of the biomass, rather than the perception of stock status.

The estimation of fishing power, δ, is an important element of the assessment model. It is only estimable with multiple fleets when at least one fleet value is specified. For anchovy the contrast in the Ghana and Togo data can be explained by a large value of δ for the Togo fleet. While this may well be real, it could also be the result of some other temporal bias not attributable to fishing power such as changes to the way data are reported or recorded. In any event, results presented here suggest that using the Togo data alone risks giving an erroneously optimistic perception of stock status.

For bonga shad, δ for the Benin fleet is less critical in determining stock status and the tail of the posterior parameter distribution overlaps with $\delta \leq 0$ and arguably could be removed from the model. The question then is whether the use of nominal effort without a correction for power will provide an overly optimistic perception of status. Although setting $\delta = 0$ for all fleets does not change the perceived status relative to MSY, it does give the most optimistic view, yet it seems highly unlikely fishing power has remained unchanged over 28 years.

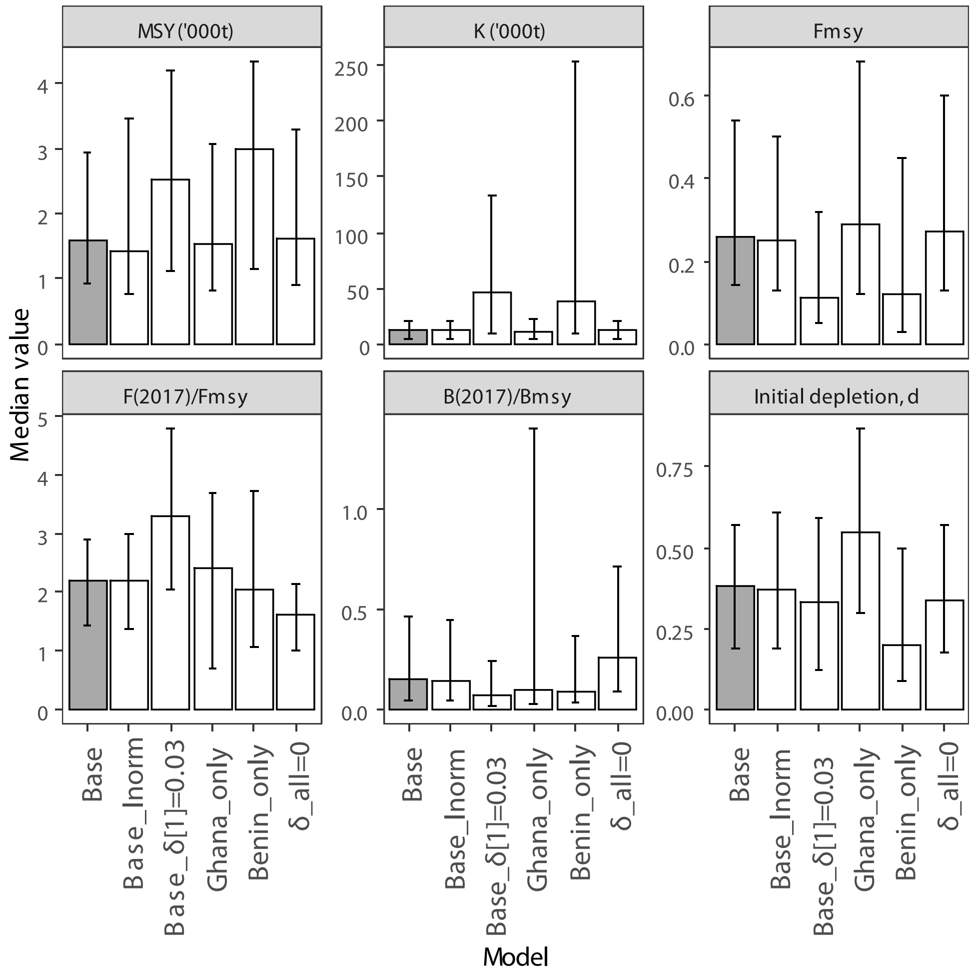

Fig. 10. Bonga shad. Sensitivity results of key parameters and quantities of interest. Bars show the median parameter value. The base model is shown in grey and sensitivity runs in white. Error bars show the 90 % credible intervals. Model definitions are given in Table 1.

Our assessment model is based on the familiar Schaefer surplus production model. This is a special case of the more general Pella-Tomlinson model with a shape parameter of 2 where the yield curve is parabolic (Pella and Tomlinson, 1969). A study by Thorson et al. (2012) suggests that the shape parameter for many taxa lies somewhat below two leading to an asymmetric yield curve. Clearly if anchovy and bonga shad production is better characterised by a lower shape parameter value this would lead to different estimates of m and K. There is insufficient information in the data to estimate the shape parameter so we have followed the conventional Schaefer approach widely used for these stocks. However, it is clear that even with the Schaefer assumption, estimates of m and K are subject to large uncertainty but nevertheless, in these stocks, the perceived status is robust. It may be possible to reduce this uncertainty by applying a prior for F_{MSY} based on life history traits as suggested by Sparholt et al. (2021).

The analyses discussed here highlight the problems of uncertainty associated with all assessments. They show that there is a need to conduct sensitivity analyses to help understand the robustness of results (Patterson et al., 2001). While the status of the bonga shad stock appears clear, the anchovy assessment is subject to greater uncertainty due to the change in perception when different data or assumptions about fishing power are made. Currently assessments of these stocks rely on a single model run and often with only a subset of the available data, chosen without a clear rationale. It is desirable to conduct additional analysis to demonstrate the robustness of assessments to the choice of data and modelling assumptions to avoid potentially poor management decisions based on a single model.

CRediT authorship contribution statement

Robin Cook: Conceptualization, Methodology, Software, Writing- Original draft preparation. **Emmanuel Acheampong:** Writing- Original draft preparation, Reviewing and Editing. **Joseph Aggrey-Fynn:** Writing- Original draft preparation, Reviewing and Editing. **Michael Heath:** Writing- Reviewing and Editing.

Author contributions

RC conceived and performed research. RC wrote the paper with contributions from EA, JA-F and MH.

Data availability

The data underlying this article are available in the CECAF working group report (FAO, 2019) and can be accessed at www.fao.org/documents/card/en/c/ca5402b.

Declaration of Competing Interest

The authors report no declarations of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.fishres.2021.106048.

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