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Some news approaches for standardizing tropical purse seiners CPUEs

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Abstract

Indices of CPUE are presented for skipjack tuna (*Katsuwonus pelamis*) for the Indian Ocean over the period 1980-2013. The analysis was initiated under the framework of the E.U. research project CECOFAD, whose objectives are to enhance our understanding of fishing effort units and improve the accuracy of purse-seine CPUE estimates. Skipjack stock assessments mainly depend on abundance indices derived from purse-seine fleets, thus standardisation of purse seiner CPUEs for this species is a priority.
We follow a CPUE definition framework where three different types of CPUE are calculated to describe trends in number of schools, school detectability and catchability and school size. CPUE standardization is typically achieved with the development of GLM models; these estimates are often biased because the range of the fishing area changes from one year to the next. We compare CPUE trends derived from conventional GLMs with trends based on GLMMs, where the spatial explanatory variables are treated as a random effect. According to a definition, a variable is random when it constitutes only a part of the entire population: spatial variables can be considered random since each year fishing vessels sample only a part of the historically fished area. Exploratory analyses revealed issues of heterogeneity and autocorrelation, supporting the use of mixed models and the shift towards a Bayesian approach to CPUE standardization modeling.
Our analysis uses fishing sets targeting free swimming tuna schools for the French purse seiners operating in the western Indian Ocean. Future work will address the problem of accounting for the major changes in purse seine fishing strategies and the implementation of new technology on board (mainly the use of FAD technology) under a Bayesian framework.

Introduction

Tropical tuna purse seine fisheries capture different species and sizes of tuna. Large yellowfin (*Thunnus albacores*), and in some strata skipjack (*Katsuwonus pelamis*), are caught in free-swimming schools, whereas skipjack, yellowfin juveniles and bigeye (*Thunnus obesus*) aggregate near natural or artificial floating objects. The European tropical tuna purse seine fishery (i.e. France and Spain) began in the early 1980s in the western Indian Ocean. Artificial drifting fish aggregating devices (DFADs) are widely used (Hallier and Parajua, 1999) and have resulted in a significant increase in skipjack catch and in catches of bigeye and yellowfin tuna juveniles.

The implementation of DFAD complicates the definition of a fishing effort unit for purse seiners because it relates to catchability, a parameter already affected by a multitude of factors. In the absence of suitable standardization of purse-seine CPUE indices, most stock assessments of tropical tunas, worldwide, rely on longline CPUE indices. The later rarely account for changes in technology and only depict the biomass of the older fraction of tuna populations. Skipjack stock assessments depend mainly on the accuracy of abundance indices obtained from purse-seine CPUEs and do not account for the introduction, onboard, of new fishing devices (Torres-Ireneo el al, 2014) or for changes in the range of the historically fished area.
Purse seiner CPUEs standardization is mainly achieved with the implementation of Generalized Linear Models (GLMs). These models provide a certain degree of flexibility and at the same time are easy to implement and interpret; however their assumptions are strict and often violated for spatiotemporal data, collected under unbalanced and non-random schemes (as is often the case with fisheries dependent data). To deal with such issues other CPUEs standardization procedures (GLMM, Bayesian methods) can be explored: integrating spatial correlation in CPUE standardization (Nishida and Chen, 2004), checking if there is a correlation between catch and effort and an additional spatial correlation (Pereira et al, 2009), and accounting for the changes in the spatial distribution of the fishing effort over time (Campbell, 2004, Hoyle et al, 2014). In the latter case – when the spatial range of the fished area is variable over time - the predicted CPUEs of periodically "unfished" areas can be integrated in the calculation of the annual index of abundance by treating spatial variables as random effects (Zhang and Holmes, 2010; Cao et al, 2011; McKechnie et al, 2013).

Increasing fishing efficiency through improvements of fishing gears is likely the main factor that strongly modifies the relationship between CPUE and abundance over time (Gaertner and Pallares, 1998; Fonteneau et al, 1999). One parameter that varies over time – as a result of fishing strategies, technological improvements of fishing efficiency and fish population dynamics - the spatial distribution of the fishing effort. It is commonly admitted that the spatial dimension of fishing activities and resources has to be accurately accounted for in the standardization process as it may severely bias the estimates of abundance indices (Walters, 2003). In this paper we compare the traditionally used CPUE standardization models, namely GLMs, with mixed models that allow us to derive standardized CPUE estimates for "unfished" areas and account for spatial heterogeneity in fishing effort.

Materials and Methods

Logbook data on the French purse seine fleet, have consistently been collected by the Institut de Recherche pour le Développement (IRD) for the period 1982-2013. Logbooks are records for each fishing set and include information on: the date; the geographic position at sea of the set; indicators of potential presence of tuna schools: natural or artificial floating object (e.g., DFAD), whale, whale-shark, or free school (noted as such when the detection was done by birds sighting); the weight and the catch composition of the targeted tuna species. For the sake of simplicity and taking into account similarities in tuna species composition and size of the fish, tuna school presence indicators are commonly classified into two main fishing modes:

free-school (true free school and whale sets) and FAD (DFAD, logs and whale-shark sets). For this analysis the data were aggregated in an 1x1 degree grid on a monthly basis.

In the traditional tuna purse seine fishery (characterized by free-swimming schools and natural floating objects), the fishing effort was expressed as searching time, i.e., the daylight hours devoted to the detection of tuna schools minus the setting times (Fonteneau, 1978). This simple definition may be criticized even for free-schools sets (e.g., due to the non-random distribution of fishing effort, the increase in fishing power over the years, etc). The implementation of DFAD - progressively equipped with electronic devices (Moreno et al, 2007; Lopez et al, 2014) and assisted by support vessels (Arrizabalaga et al, 2001, Pallares et al, 2002) - have broken the link between searching time and effective fishing effort for FAD sets. Remote detection of satellite-tracked FADs equipped with echo-sounder buoys often allows fishers to move directly towards a buoy, sometimes at night, avoiding or significantly reducing searching time (Fonteneau et al, 1999). These changes have major consequences for our ability to calculate useful CPUE values for these fisheries. Consequently, instead of considering a whole CPUE (e.g., expressed as a catch per searching time) in this paper we will explore different and complementary catch rates.

Based on the conclusions of the U.E. Research Project ESTHER (Gaertner and Pallares, 1998), for a better understanding on the specific impact of the new technologies introduced on board, the CPUE can be decomposed into several sub-indices. Here we follow the approach developed by Chassot et al. (2012) for standardizing CPUEs of yellowfin in free schools in the Indian Ocean. The first CPUE index (noted throughout the paper as “CPUE 1”) is defined as the total number of sets per fishing day and, depicts the ability to detect a concentration of tuna schools. The second CPUE index (CPUE 2) refers to the proportion of successful sets (sets when skipjack was caught) and describes the ability of catching a school. Finally, the third CPUE (CPUE 3) is the amount of catch per positive set, an index that combines a proxy of the size of the school with the ability to maximize a catch during the setting. The decrease in skipjack free-schools, observed since the development of the FAD fishery, likely does not depict a concomitant change in abundance (Fonteneau et al, 2000). However, we assumed that modeling the different catch rates built from free school data may provide an insight on the changes in fishing efficiency of the purse seine fleet.

Purse seiner CPUEs standardization process is traditionally achieved for each fishing mode separately: free school sets or FAD sets (Soto et al, 2009a; Soto et al, 2009b, respectively) with the use of GLM. We compare GLM and GLMM standardized CPUE estimates. The spatial explanatory variables in GLMMs are treated as random effects to account for spatial heterogeneity in fishing effort. A quantity is random when it consists of a number of units/categories, but not all units/categories are observed. A random effect allows us to draw conclusions for all possible units/categories of the variable rather than for the observed units/categories. In the case of fisheries logbooks different areas are fished (sampled) on an annual basis. By treating space as a random effect we make inference for the potentially fished area rather than the realized fished area, thus improving the comparability of annual standardized CPUE estimates.

The main explanatory variables mentioned in literature to fit nominal tropical purse seine CPUEs using GLMs are: Year, Quarter, Area, a factor termed CatPais (combining the flag and the carrying capacity of the vessel), the age of the vessel, a factor reflecting the proportion of the species targeted in the catch and the interactions between the main factors. We focus on free school sets recorded in logbooks of the French purse seine fleet operating in the Indian Ocean, therefore the factor CatPais is rendered redundant and the variables used are Year, Monsoon Season, vessel age and spatial variables (grid cell and Longhurst based eco-geographical areas). The grid cell variable can be treated as both a factor and a continuous variable (geographical coordinates of the centre of the cell): GLMs with both types of the variable were developed and compared; in GLMMs the grid cell was treated as a factor. First order interactions between variables were tested and the Null model was formed according to our prior knowledge of the system and our research goals (i.e. the investigation of spatial heterogeneity and the role of spatial variables in CPUE standardization). Model selection was achieved using Information Criteria (AIC, BIC) and model diagnostic plots.

GLMs and GLMMs were developed for all three CPUE indices described above. CPUE 1 (catch per fishing day) follows a zero-inflated log-normal distribution and was therefore modeled following the delta-lognormal method (Lo et al, 1992). The index is calculated as the product of annual estimates derived from a lognormal model (for the positive CPUEs) and a binomial model (for the proportion of days with catch). To account for unbalanced designs, the Least squares means were computed for each factor.

GLMMs were developed using the lme4 R package (Bates, 2005; Bates et al., 2013) and least squares means estimates were calculated using the lsmeans R package (Lenth, 2014). Maps were drawn using ArcGIS 10.2 (ESRI, 2011).

Results

Predictions of positive sets per searching day (CPUE1) derived from GLMs and GLMMs generally follow the same trend as observed annual averages (Fig 1). The standardized values derived from the GLM are in general lower than the nominal values whereas the GLMM predictions are higher than the nominal values at the beginning of the time series (1980s) and lower at the end (after 2008). Contractions and expansions of the fishery could explain the difference between model predictions and nominal values. At the beginning of the fishery a very small area is sampled and fishing efficiency is low, therefore lower CPUE values might be observed than those expected. As efficiency increases and the fished area expands, standardized CPUE values will be lower than nominal values.

Nominal values of the proportion of positive sets (CPUE2) are to some degree higher than the standardized time series (Fig 2). The GLM and GLMM values are close but the GLMM confidence intervals are larger than the GLM derived confidence intervals. GLMs account for the process error only whereas GLMMs add the variation of the random effect to the process error. In this case, the additional uncertainty stems from spatial heterogeneity of fishing effort (i.e. variation between sampling sites/ grid cells).

Standardized estimates of catch per set (CPUE3) are lower than the observed annual averages derived from catches. GLMM estimates coincide with the lower 95% confidence interval of the corresponding GLM derived estimates (Fig 3). The difference in estimates is particularly evident during the period 2000-2008, a prolonged period of high CPUE3 values and little inter-annual variability. the same phenomenon was demonstrated by Cao et al. (2011) for the squid jigging fishery, where CPUE predictions including unfished areas were lower than observed values or model estimates that did not account for unfished areas. Cao et al. (2011) attribute their results to the efficiency of fishing vessels in finding productive fishing grounds, and view lower standardized CPUE values as a sign of hyperstability. Similarly Zhang and Holmes (2010) developed a Bayesian model for tuna CPUE standardization, incorporating spatial variables as random effects; the authors observed a difference between model estimates (low) and nominal catches (high) related with the contraction of the fishery.

The index of sets per searching day (CPUE1) for winter is the result of stationary processes (mean and variance remain constant over time), with persistently higher values (two sets per searching day) compared with the other seasons (Fig 4). The post-monsoon season index shows great inter-annual variability with abrupt increases of the number of sets to four per searching day and precipitous decreases to near zero values the next year. A common pattern between all seasons is the high index values during the last 2-3 years of the time series (2010-2013). The proportion of positive sets (CPUE2) shows a gradually decreasing trend during all seasons (Fig 5), with the exception of the pre-monsoon season, when the index is stable with half of the sets showing positive catches for skipjack. The post-monsoon index is highly variable with peaks that seem to be periodical (three-4 year cycles). Finally, catch per set (CPUE3; Fig 6) shows similar trends in all seasons; the main characteristic is a prolonged period of high values starting in the mid 1990s until the end of the time series (around 2010).

Maps of fishing effort distribution, namely total number of sets, show a shift of fishing effort to the west (Figs 7 and 8) between the 1990s and the 2000s and a southward expansion. The shift is pronounced in the winter and the monsoon season. In addition to the expansion of the fishing grounds over the years, a sudden change in spatial distribution is observed in 2008 due to piracy off Somalia. To address security issues, fishing companies defined in 2008 a large exclusion zone off the Somali coast that represented more than 25% of the total catch of the fishery during 2001-2007. The exclusion zone resulted in some reallocation of the European fleet toward the eastern part of the North equatorial area during the typical season of FAD-fishing (June-November) in the Somali basin (Chassot et al, 2010).

Discussion

The first CPUE index (CPUE1: positive sets per searching day) is not species specific but relates to the presence of tuna schools and their detectability. The values might be variable at a seasonal and annual basis but at a multi-annual scale the time series is stationary. The other two CPUE indices (2 and 3) refer specifically to skipjack tuna and show a decreasing trend after 2007. A collapse of catches of skipjack in free swimming schools after 2007 has already been described by Fonteneau (2014) and Marsac and Floch (2014). The latter discuss the role of new fishing technologies and the environment, as drivers of the observed trends.

Although the general trends of CPUE indices are similar, regardless the standardization technique used, the amplitude of inter-annual variability and the running average differ between CPUE time series derived through different standardization methods. CPUE values derived from GLM standardization approaches that do not account for changes in the distribution of fishing effort are expected to be biased because CPUE varies between fished areas and fishing cannot be considered random sampling (Campbell, 2004; Hoyle and Okamoto, 2011; McKechnie et al., 2013). Un-standardized and GLM-standardized CPUEs are expected to overestimate CPUEs; the phenomemon is related either with the expansion of a fishery and the discovery of new, unexploited, productive areas or its contraction to areas where CPUE is highest (hyperstability) (McKechnie et al., 2013). In this paper we show how to account for spatial heterogeneity of fishing effort through mixed modeling and discuss the effect this approach has on standardized CPUE values.

Treating spatial variables as random effects in a mixed model or Bayesian framework has been suggested as a means to derive realistic CPUE values and related uncertainty for fisheries that undergo changes (contractions/ expansions) of fishing effort distribution (Campbell, 2004, 2015; Cao et al., 2011; Maunder and Punt, 2004; Zhang and Holmes, 2010). When sampling sites (i.e. fished areas, in this case grid cells or larger sampling areas where fishing effort is present) are fixed factors, annual CPUE predictions are restricted to the sites that were fished on the specific year. Areas historically fished or with the potential of being fished are overlooked. GLMMs do not focus on the separate levels of a factor but on the variance of the distribution from which the levels are assumed to originate (Bolker et al., 2009; McCulloch and Neuhaus, 2001; Venables and Dichmont, 2004). Therefore GLMMs, with "site" as a random effect, allow for CPUE predictions outside the fished areas, in sites that are not sampled. The flexibility of GLMMs is offset by the higher uncertainty of predictions. If the sampling sites are fixed, the estimated error equals the error per site; by randomizing the sites the estimated error incorporates variability stemming from two sources: within each sampled site and the between sites. The certainty on our prediction is reduced by our aspiration to generalize inference beyond the sampled sites, to the "population" of possible sites. A conspicuous example of this effect is seen in this study for the standardized values of the proportion of positive sets (CPUE2; Fig 2).

In this paper we explored the issue of spatial heterogeneity of fisheries dependent data, if it effects CPUE estimates and how this affect can be dealt with through non-conventional CPUE standardising approaches. However this exploratory analysis brought more problems to light. First, from a statistical point of view logbook data are derived through a very complex sampling design. As discussed earlier the sampling scheme is non-random; on top of that the data are correlated in space and time, they are heteroscedastic and hierarchical (e.g. at a vessel level) and they don't fit well into conventional distributions (Candy, 2004; Nishida and Chen, 2004). These issues can be addressed under a GLMM or Bayesian framework. Second, the choice of CPUE is often arbitrary and its relationship to abundance and fishing efficiency is still not fully understood. Here we follow the framework suggested by Chassot et al., (2012), where different definitions of CPUE provide a holistic description of the fishery and the fished stocks. Third, thought should be put into the definition of the study area and the criteria (historial, biological, statistical) that should be followed to delimit it. Finally, the development of FADs and the incorporation of such technological developments - with unknown effects on fishing effort and on the ecosystem - into CPUE standardization models is essential and constitutes a research priority. Future work aims to further investigate the identified problems and find ways to improve CPUE indices for the purse seine fishery.

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Fig 1. Annual predictions for sets per searching day (CPUE1) derived from a GLM and a GLMM. The latter accounts for "unfished" areas. 95% Confidence intervals are also shown (dashed lines) and the observed annual average is given.

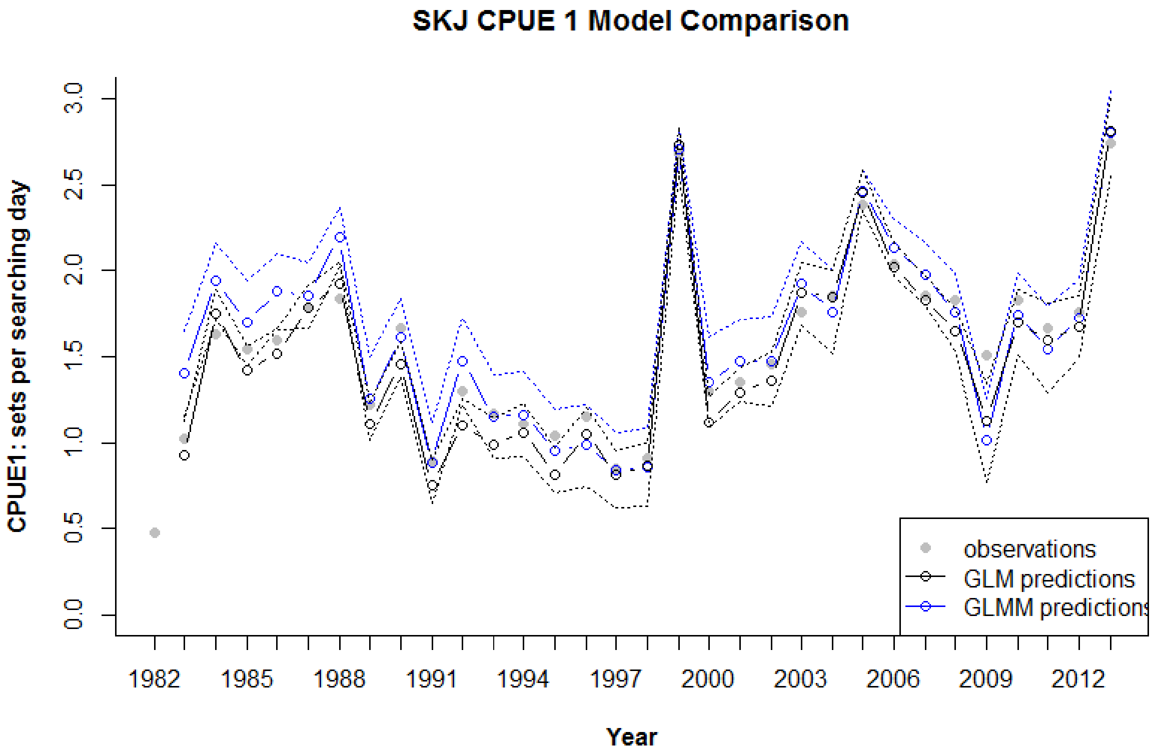

Fig 2. Annual proportion of positive sets (CPUE2) derived from a GLM and a GLMM. The latter accounts for "unfished" areas. 95% Confidence intervals are also shown (dashed lines) and the observed annual average is given.

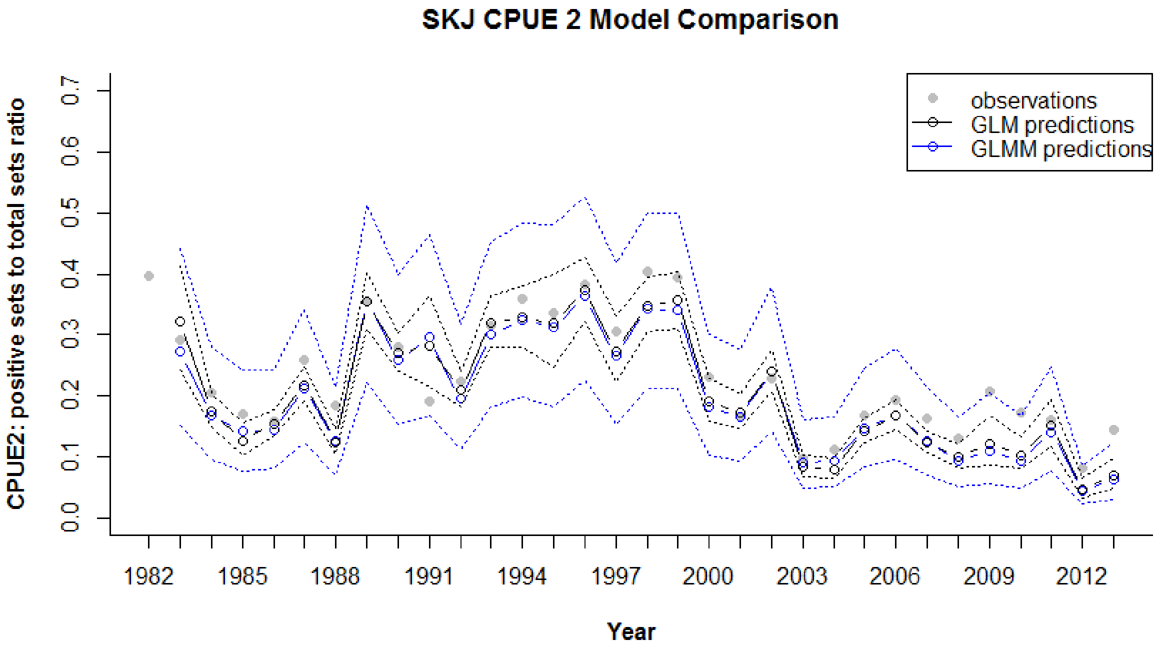

Fig 3. Annual predictions for skipjack catch per positive set (CPUE3) derived from a GLM and a GLMM. The latter accounts for "unfished" areas. 95% Confidence intervals are also shown (dashed lines) and the observed annual average is given.

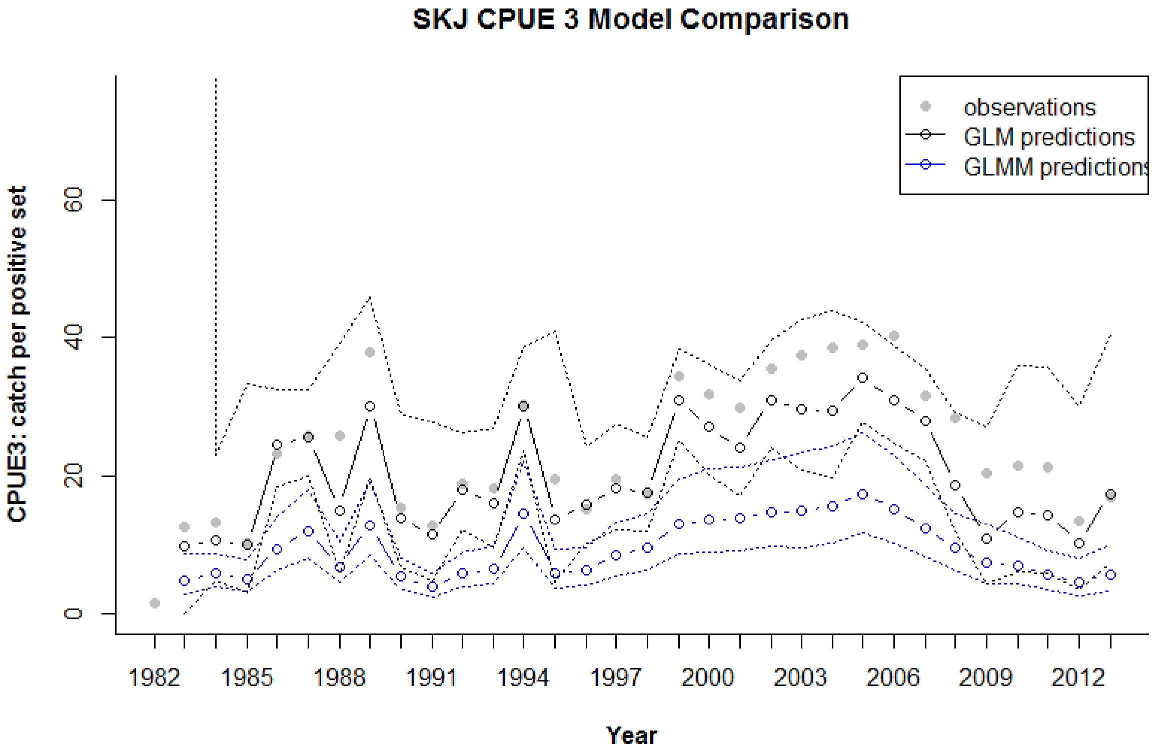

Fig 4. Sets per searching day (CPUE1) trends for skipjack, standardised using a GLMM that accounts for spatial heterogeneity of fishing effort and makes predictions for "unfished" areas.

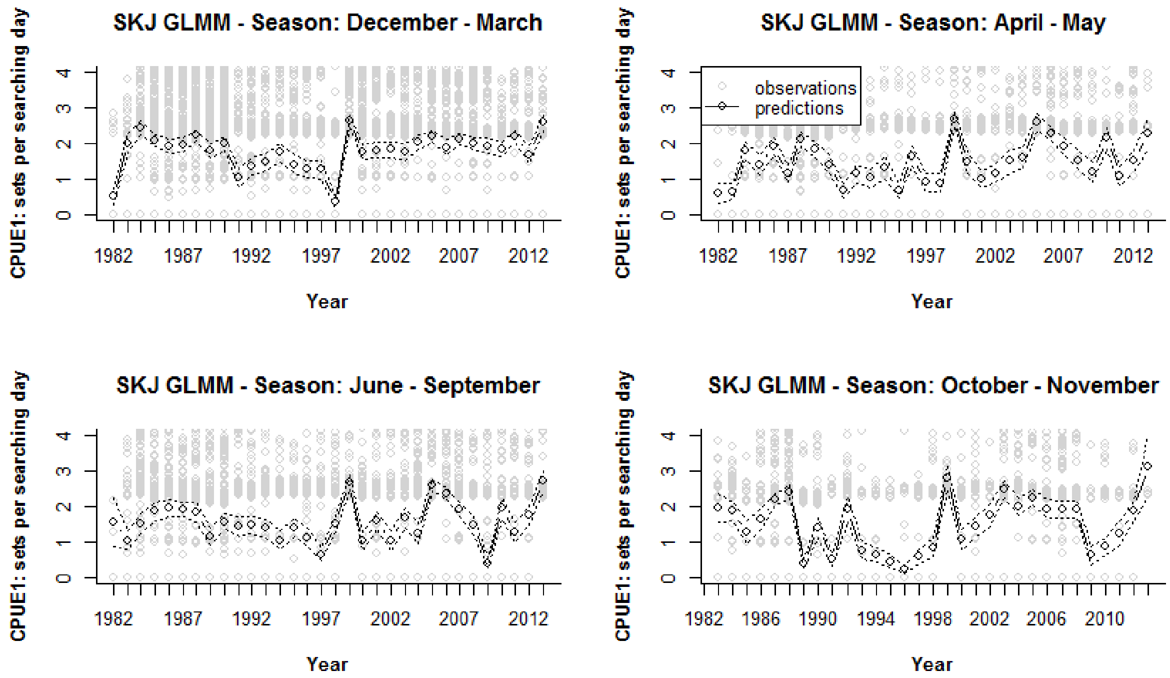

Fig 5. Proportion of positive sets (CPUE2) trends for skipjack, standardised using a GLMM that accounts for spatial heterogeneity of fishing effort and makes predictions for "unfished" areas.

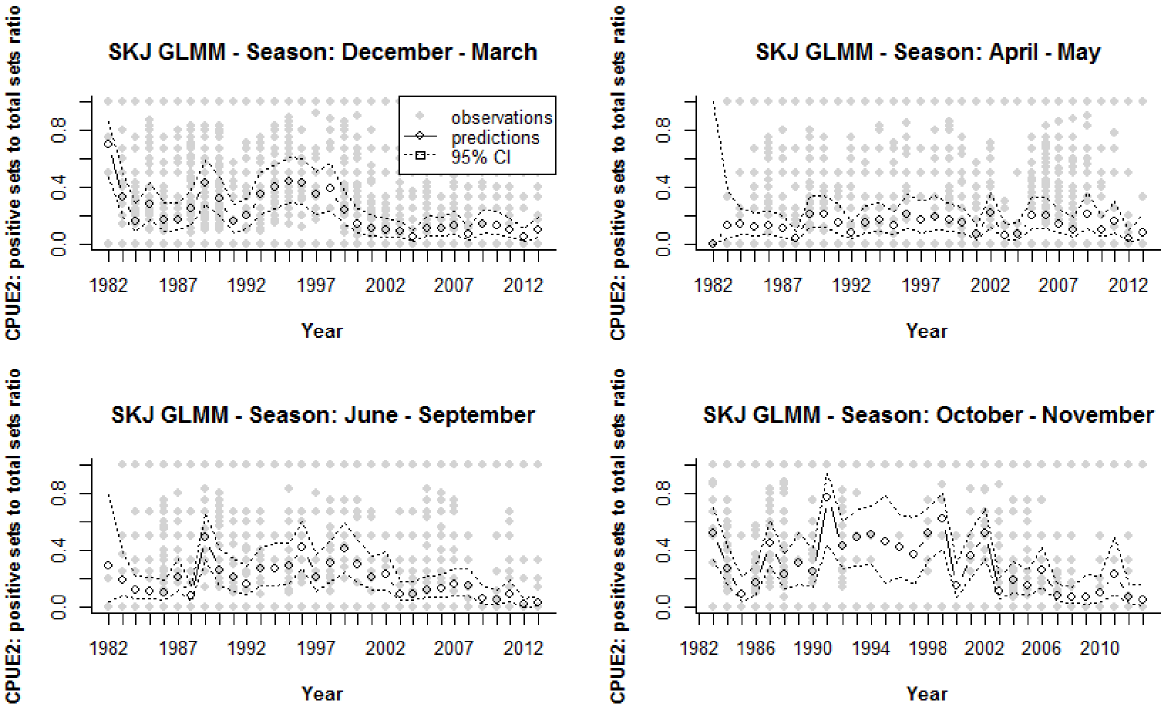

Fig 6. Catch per positive set (CPUE3) trends for skipjack, standardised using a GLMM that accounts for spatial heterogeneity of fishing effort and makes predictions for "unfished" areas.

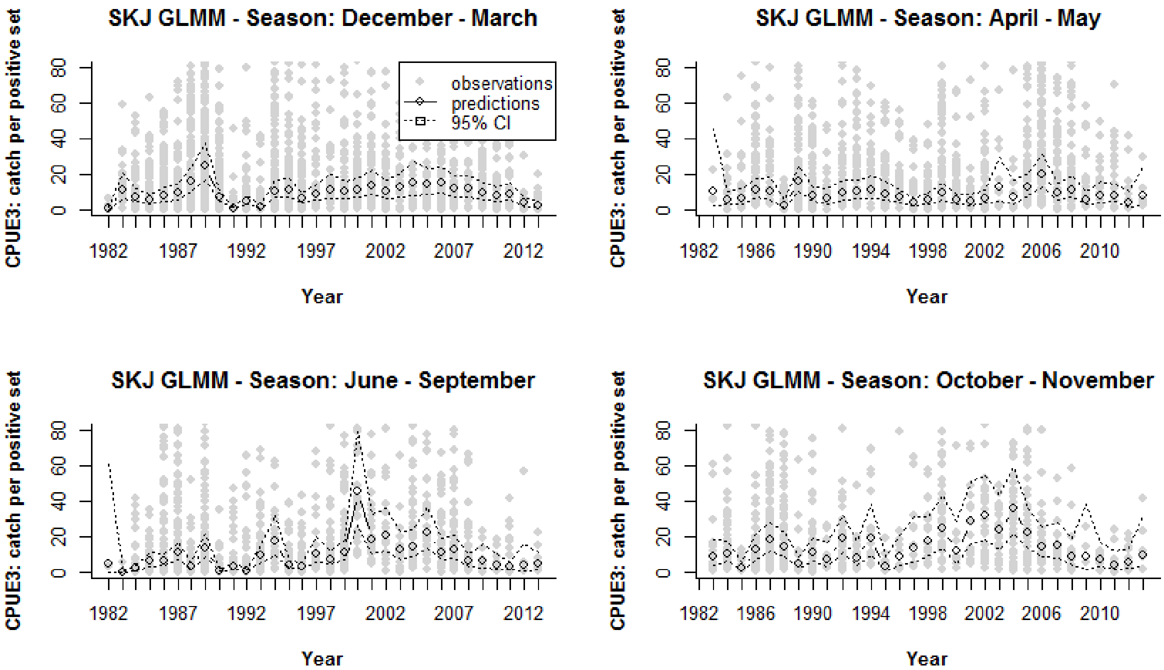

Fig 7. Maps of fishing effort distribution (total number of sets) for 2 decades (90s and 00s) per season. Fishing effort has contracted from the East and expanded in the west.